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Effect of repair models on risk-based optimal inspection strategies for support structures of offshore wind turbines

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ABSTRACT: Owners or operators of offshore wind farms perform inspections to collect information on the condition of the wind turbine support structures and perform repairs if required. These activities are costly and should be optimized. Risk-based methods can be applied to identify inspection and repair strategies that ensure an optimal balance between the expected total service life cost of inspection and repair, and the achieved risk reduction. Such an optimization requires explicit modeling of repairs. In this paper, the impact of different repair models on the results of a risk-based optimization of inspection and repair strategies is quantified in a numerical example considering a jacket-type steel frame subject to high-cycle fatigue. The example showed that, in this specific application, there is no need for detailed modeling of the behavior of repaired welded connections.

1 INTRODUCTION

Supports structures of offshore wind turbines are subject to various deterioration processes, which may have an adverse effect on their performance. To maintain an adequate performance throughout a support structure's service life, some of its components may have to be repaired. In a risk-based approach, repairs are planned such that their expected cost is optimally balanced with the achieved reduction in the expected cost of structural system failure (risk). To enable an improved condition-based or predictive planning of repairs, information on the condition of structural systems can be collected through inspections. They also come at a price and should therefore also be optimized.

The problem of jointly optimizing inspections and repairs of deteriorating structural systems is a sequential decision problem (Raiffa and Schlaifer 1961; Kochenderfer 2015), because decisions are made at multiple points in time, at which different amounts of information are available. To solve this computationally challenging problem at the structural system level, Luque and Straub (2019) propose a framework based on a direct policy search, which originates from the field of artificial intelligence (Kochenderfer 2015). In this approach, system-wide inspection and repair strategies are defined in terms of decision rules which deterministically prescribe whether, what and how to inspect and repair conditional on all available information at the different decision times. For each defined strategy, the expected total service life cost consisting of the expected cost of inspection, repair and structural system failure is computed using Monte Carlo simulation (MCS) based on samples of potential inspection and repair histories. The optimal strategy among the pre-selected strategies minimizes the expected total service life cost.

As part of the MCS, the time-dependent reliability of the deteriorating structural system is computed many times for different potential inspection and repair histories. The analysis accounts for system effects arising from (a) the correlation among deterioration states of different structural components, (b) the interaction between component deterioration and system failure and (c) the indirect information on the condition of structural components obtained by inspecting the condition of some of the system's components. The analysis also captures the effect of repairs. In the past, simple models, in which a repaired component is, for example, represented by a model identical to a new component and treated as stochastically independent of the component before the repair, have been utilized in risk-based planning of inspections at the component level (Straub and Faber 2006). To substantiate that simple repair models are also applicable to the risk-based optimization of inspection and repair strategies at the structural system level, the impact of different repair models on the outcome of such analyses is studied by means of a numerical example considering – in analogy to a jacket support structure – a jacket-type steel frame subject to high-cycle fatigue.

2 RISK-BASED OPTIMIZATION OF INSPECTION AND REPAIR STRATEGIES USING DIRECT POLICY SEARCH

The finite service life of a deteriorating structural system is divided into intervals $j = 1, \dots, m$ such that the jth interval corresponds to $t \in (t_{j-1}, t_j]$. The length of each interval is chosen to be one year (which is a typical choice). In each year j, a policy π_j – a set of rules – is adopted that deterministically prescribes which actions should be taken conditional on the history of observations and actions up to that year. The set of all policies adopted in the different years $\mathcal{S} = \{\pi_j\}_{j=1}^{m}$ is a strategy.

Throughout a structure's service life, different costs are incurred. The total service life cost C_T may be defined as the sum of the total cost of (1) launching the inspection campaigns C_C, (2) performing component inspections C_I, (3) performing component repairs C_R and (4) structural failure R_F (risk). It can be written in function of a strategy $\mathcal{S}$ and corresponding probabilistic inspection data $\mathbf{Z} = [\mathbf{Z}_1^T, \dots, \mathbf{Z}_j^T, \dots, \mathbf{Z}_m^T]^T$ as:

$$C_T(\mathcal{S}, \mathbf{Z}) = C_C(\mathcal{S}, \mathbf{Z}) + C_I(\mathcal{S}, \mathbf{Z}) + C_R(\mathcal{S}, \mathbf{Z}) + R_F(\mathcal{S}, \mathbf{Z}) \tag{1}$$

where $\mathbf{Z}_j$ are the probabilistic inspection data in year j. The expected value of the total service life cost for a strategy $\mathcal{S}$ with respect to $\mathbf{Z}$ can be written as:

$$\mathbb{E}_{\mathbf{Z}}[C_T(\mathcal{S}, \mathbf{Z})] = \mathbb{E}_{\mathbf{Z}}[C_C(\mathcal{S}, \mathbf{Z}) + C_I(\mathcal{S}, \mathbf{Z}) + C_R(\mathcal{S}, \mathbf{Z})] + \mathbb{E}_{\mathbf{Z}}[R_F(\mathcal{S}, \mathbf{Z})] \tag{2}$$

The first term of the right-hand side of Eq. (2) is obtained as:

$$\begin{aligned}&\mathbb{E}_{\mathbf{Z}}[C_C(\mathcal{S}, \mathbf{Z}) + C_I(\mathcal{S}, \mathbf{Z}) + C_R(\mathcal{S}, \mathbf{Z})] \\ &= \int_{\Omega_{\mathbf{Z}}(\mathcal{S})} \left[\sum_{i=1}^{n_C(\mathcal{S}, \mathbf{z})} \left[c_C + n_{I,i}(\mathcal{S}, \mathbf{z})\, c_I + n_{R,i}(\mathcal{S}, \mathbf{z})\, c_R\right] \cdot \gamma(t_i) \cdot [1 - \Pr[F(t_i) | \mathcal{S}, \mathbf{z}]] \right] p(\mathbf{z}) \mathrm{d}\mathbf{z}\end{aligned} \tag{3}$$

wherein $p(\mathbf{z})$ is the probability distribution of the inspection data $\mathbf{Z}$ with support $\Omega_{\mathbf{Z}}(\mathcal{S})$, which is a function of the strategy $\mathcal{S}$; $n_C(\mathcal{S}, \mathbf{z})$ is the total number of inspections campaigns; t_i is the time at the end of the interval in which the ith inspection campaign is performed; $n_{I,i}(\mathcal{S}, \mathbf{z})$ and $n_{R,i}(\mathcal{S}, \mathbf{z})$ are the numbers of inspected and repaired components during the ith campaign; c_C, c_I and c_R are the unit costs of launching an inspection campaign, inspecting and repairing a component; $\gamma(t_i) = 1/(1+r)^{t_i}$ is the discount function that discounts the cost to its present value, where r is the discount rate; and $1 - \Pr[F(t_i) | \mathcal{S}, \mathbf{z}]$ is the probability of system survival up to time t_i conditional on the inspection data $\mathbf{Z} = \mathbf{z}$ and corresponding repairs as determined by the strategy $\mathcal{S}$. For highly reliable systems such as wind turbine support structures, $1 - \Pr[F(t_i) | \mathcal{S}, \mathbf{z}]$ will be close to one. Hence, $\mathbb{E}_{\mathbf{Z}}[C_C(\mathcal{S}, \mathbf{Z}) + C_I(\mathcal{S}, \mathbf{Z}) + C_R(\mathcal{S}, \mathbf{Z})]$ may be approximated as:

$$\mathbb{E}_{\mathbf{Z}}[C_C(\mathcal{S},\mathbf{Z}) + C_I(\mathcal{S},\mathbf{Z}) + C_R(\mathcal{S},\mathbf{Z})] \approx \int_{\Omega_{\mathbf{Z}}(\mathcal{S})} \underbrace{\left[\sum_{i=1}^{n_C(\mathcal{S},\mathbf{z})} \left[c_C + n_{I,i}(\mathcal{S},\mathbf{z})\, c_I + n_{R,i}(\mathcal{S},\mathbf{z})\, c_R\right] \cdot \gamma(t_i)\right]}_{\approx C_C(\mathcal{S},\mathbf{z})+C_I(\mathcal{S},\mathbf{z})+C_R(\mathcal{S},\mathbf{z})} p(\mathbf{z})\mathrm{d}\mathbf{z} \tag{4}$$

The expected total failure cost for a strategy $\mathcal{S}$ is determined as:

$$\begin{aligned}\mathbb{E}_{\mathbf{Z}}[R_F(\mathcal{S},\mathbf{Z})] &= \int_{\Omega_{\mathbf{Z}}(\mathcal{S})} \left[\sum_{j=1}^{m} c_F \cdot \gamma(t_j) \cdot \left[\Pr[F(t_j)|\mathcal{S},\mathbf{z}] - \Pr[F(t_{j-1})|\mathcal{S},\mathbf{z}]\right]\right] p(\mathbf{z})\mathrm{d}\mathbf{z} \\ &= c_F \sum_{j=1}^{m} \gamma(t_j) \left[\int_{\Omega_{\mathbf{Z}}(\mathcal{S})} \Pr[F(t_j)|\mathcal{S},\mathbf{z}]\, p(\mathbf{z})\mathrm{d}\mathbf{z} - \int_{\Omega_{\mathbf{Z}}(\mathcal{S})} \Pr[F(t_{j-1})|\mathcal{S},\mathbf{z}]\, p(\mathbf{z})\mathrm{d}\mathbf{z}\right]\end{aligned} \tag{5}$$

wherein c_F is the cost of system failure, $\Pr[F(t_j)|\mathcal{S},\mathbf{z}]$ is the conditional probability of system failure up to time t_j and $\Pr[F(t_j)|\mathcal{S},\mathbf{z}] - \Pr[F(t_{j-1})|\mathcal{S},\mathbf{z}]$ is the conditional probability of system failure in $(t_{j-1}, t_j]$. Both probabilities are conditional on the inspection data $\mathbf{Z} = \mathbf{z}$ and corresponding repairs as prescribed by the strategy $\mathcal{S}$.

The probability distribution of the inspection data $\mathbf{Z}$ can be factorized as $p(\mathbf{z}) = p(\mathbf{z}_{j:m}|\mathbf{z}_{1:j-1})\, p(\mathbf{z}_{1:j-1})$. Thus, the expected value of $\Pr[F(t_j)|\mathcal{S},\mathbf{z}]$ can be written as:

$$\begin{aligned}&\int_{\Omega_{\mathbf{Z}}(\mathcal{S})} \Pr[F(t_j)|\mathcal{S},\mathbf{z}]\, p(\mathbf{z})\mathrm{d}\mathbf{z} \\ &= \int_{\Omega_{\mathbf{Z}_{1:j-1}}(\mathcal{S})} \left[\int_{\Omega_{\mathbf{Z}_{j:m}}(\mathcal{S})} \Pr[F(t_j)|\mathcal{S},\mathbf{z}_{1:j-1},\mathbf{z}_{j:m}]\, p(\mathbf{z}_{j:m}|\mathbf{z}_{1:j-1})\, \mathrm{d}\mathbf{z}_{j:m}\right] p(\mathbf{z}_{1:j-1})\mathrm{d}\mathbf{z}_{1:j-1}\end{aligned} \tag{6}$$

The probability of system failure up to time t_j depends only on the repairs performed before that time. Hence, the conditional expected value of $\Pr[F(t_j)|\mathcal{S},\mathbf{z}]$ with respect to $\mathbf{Z}_{j:m}$ given $\mathbf{Z}_{1:j-1} = \mathbf{z}_{1:j-1}$ – the inner most integral in Eq. (6) – is equal to $\Pr[F(t_j)|\mathcal{S},\mathbf{z}_{1:j-1}]$. From this it can be shown that $\mathbb{E}_{\mathbf{Z}}[R_F(\mathcal{S},\mathbf{Z})]$ can be obtained as:

$$\mathbb{E}_{\mathbf{Z}}[R_F(\mathcal{S},\mathbf{Z})] = \int_{\Omega_{\mathbf{Z}}(\mathcal{S})} \underbrace{\left[c_F \sum_{j=1}^{m} \gamma(t_j) \cdot \left[\Pr[F(t_j)|\mathcal{S},\mathbf{z}_{1:j-1}] - \Pr[F(t_{j-1})|\mathcal{S},\mathbf{z}_{1:j-1}]\right]\right]}_{=R_F(\mathcal{S},\mathbf{z})\text{ (see also Luque and Straub 2019)}} p(\mathbf{z})\mathrm{d}\mathbf{z} \tag{7}$$

The optimal strategy $\mathcal{S}^*$ minimizes the expected total service life cost, i.e.:

$$\mathcal{S}^* = \arg\min_{\mathcal{S}}(\mathbb{E}_{\mathbf{Z}}[C_T(\mathcal{S},\mathbf{Z})]) \tag{8}$$

The identification of $\mathcal{S}^*$ is challenging due to (a) the computation of the conditional system failure probabilities $\Pr[F(t_j)|\mathcal{S},\mathbf{z}_{1:j-1}]$ required to evaluate the conditional total failure cost $R_F(\mathcal{S},\mathbf{z})$, and (b) the large number of possible strategies. The first challenge is briefly discussed in Section 3. The second is addressed by employing a direct policy search that explores a subset of strategies, which is selected using a heuristic approach (Luque and Straub 2019). In this approach, a strategy is defined in terms of parameterized decision rules that prescribe actions at each decision time given the entire history of observations and actions up to this decision. An example of such rules is provided in the numerical example in Section 4.

Let $\boldsymbol{\theta}$ be the heuristic parameters of the rules defining the strategy denoted by $\mathcal{S}_{\boldsymbol{\theta}}$. The optimal strategy $\mathcal{S}^*$ is approximated by $\mathcal{S}_{\boldsymbol{\theta}^*}$, where $\boldsymbol{\theta}^*$ is obtained as:

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}}(\mathbb{E}_{\mathbf{Z}}[C_T(\mathcal{S}_{\boldsymbol{\theta}}, \mathbf{Z})]) \tag{9}$$

$\mathbb{E}_{\mathbf{Z}}[C_T(\mathcal{S}_{\boldsymbol{\theta}}, \mathbf{Z})]$ is estimated using MCS:

$$\mathbb{E}_{\mathbf{Z}}[C_T(\mathcal{S}_{\boldsymbol{\theta}}, \mathbf{Z})] \approx \frac{1}{n}\sum_{i=1}^{n} C_T(\mathcal{S}_{\boldsymbol{\theta}}, \mathbf{z}^{(i)}) \tag{10}$$

wherein $\{\mathbf{z}^{(i)}\}_{i=1}^{n}$ are samples of the inspection data $\mathbf{Z}$ and corresponding repairs as prescribed by $\mathcal{S}_{\boldsymbol{\theta}}$. They can, for example, be generated as described in (Schneider et al. 2018).

3 RELIABILITY ANALYSIS OF DETERIORATING STRUCTURAL SYSTEMS

In structural reliability, the reliability of deteriorating structural systems is assessed by means of physics-based probabilistic models that describe the deterioration processes and structural performance. The assessment requires the solution of a time-variant reliability problem because the demand on and the capacity of deteriorating structures change with time. In most applications, as discussed in (Straub et al. 2019), the deteriorating capacity of structural systems can be modeled as statistically independent of the demand. In this case, a time-discretized approach can be employed in which the time-variant reliability problem is transformed into a series of time-invariant reliability problems.

To illustrate this approach, consider the case in which the demand on the structural system can be described by a scalar load process $\{S(t)\}$ and the structural capacity with respect to this load process is $\{R(\mathbf{X}_R, t)\}$. The stochastic parameters $\mathbf{X}_R$ include the parameters of the deterioration model. In a time-discretized approach, the service life of a structure is divided into intervals as described in Section 2 and an interval failure event F_j^* is defined as the event of system failure in $(t_{j-1}, t_j]$ neglecting the possibility that the system may have failed earlier (Straub et al. 2019):

$$F_j^* = \{\exists \tau \in (t_{j-1}, t_j] : R(\mathbf{X}_R, \tau) \leq S(\tau)\} \tag{11}$$

An exact computation of the corresponding probability $\Pr(F_j^*)$ requires the solution of a time-variant reliability problem, but if $\{S(t)\}$ and $\{R(\mathbf{X}_R, t)\}$ are statistically independent, $\Pr(F_j^*)$ can be approximated as:

$$\Pr(F_j^*) \approx \Pr[R(\mathbf{X}_R, t_j) \leq S_{max,j}] \tag{12}$$

wherein $R(\mathbf{X}_R, t_j)$ is the structural capacity at the end of jth interval and $S_{max,j}$ is the maximum demand in that interval. The distribution of $S_{max,j}$ is determined by an extreme value analysis. Eq. (12) corresponds to a time-invariant reliability problem.

The event of failure up to time t_j is the union of the interval failure events up to that time:

$$F(t_j) = F_1^* \cup F_2^* \cup \ldots \cup F_j^* \tag{13}$$

An intuitive (but not necessarily computationally optimal) approach to compute the probability of $F(t_j)$ is to describe this event by the equivalent limit state function:

$$g_{1:j}(\mathbf{X}) = \min_{i \in \{1,\ldots,j\}} g_i(\mathbf{X}) \tag{14}$$

where $\mathbf{X} = [\mathbf{X}_R^T, S_{max,1}, \dots, S_{max,m}]^T$ and $g_i(\mathbf{X}) = R(\mathbf{X}_R, t_i) - S_{max,i}$ is the limit state function describing the ith interval failure event F_i^*. The probability of $F(t_j)$ can then be evaluated by integrating the joint probability distribution of $\mathbf{X}$ over the failure domain:

$$\Pr[F(t_j)] = \Pr[F_1^* \cup F_2^* \cup \dots \cup F_j^*] = \int_{g_{1:j}(\mathbf{X}) \leq 0} p(\mathbf{x})\,\mathrm{d}\mathbf{x} \tag{15}$$

The simplest and most robust method for solving the integral in Eq. (15) is MCS – a sampling-based structural reliability method (SRM) (Ditlevsen and Madsen 1996). The disadvantage of MSC is its inefficiency in computing rare event probabilities. More efficient solution strategies for computing $\Pr[F(t_j)]$ are proposed in (Straub et al. 2019).

Inspection data $\mathbf{Z} = \mathbf{z}$ provide direct or indirect information on (some of) the stochastic parameters $\mathbf{X}$ of the limit state function $g_{1:j}$. In a probabilistic setting, the data can be applied to update the probability distribution of $\mathbf{X}$ from $p(\mathbf{x})$ to $p(\mathbf{x}|\mathbf{z})$ using Bayes' theorem:

$$p(\mathbf{x}|\mathbf{z}) \propto L(\mathbf{x}|\mathbf{z})\, p(\mathbf{x}) \tag{16}$$

wherein $L(\mathbf{x}|\mathbf{z}) \propto p(\mathbf{z}|\mathbf{x})$ is the likelihood function describing the inspection data. The inspection data do not necessarily provide information on all parameters in $\mathbf{X}$. Those parameters cannot be learned, i.e. the likelihood function $L(\mathbf{x}|\mathbf{z})$ is constant with respect to those parameters.

The conditional probability of $F(t_j)$ given the inspection data $\mathbf{Z} = \mathbf{z}$ is obtained by replacing $p(\mathbf{x})$ with $p(\mathbf{x}|\mathbf{z})$ in Eq. (15):

$$\Pr[F(t_j)|\mathbf{z}] = \Pr[F_1^* \cup F_2^* \cup \dots \cup F_j^*|\mathbf{z}] = \int_{g_{1:j}(\mathbf{X}) \leq 0} p(\mathbf{x}|\mathbf{z})\,\mathrm{d}\mathbf{x} \tag{17}$$

Generally, closed-form solutions of $p(\mathbf{x}|\mathbf{z})$ are not available and most SRM cannot be applied to solve Eq. (17). Straub et al. (2016) propose a framework called BUS (Bayesian Updating with Structural reliability methods) that enables the evaluation of Eq. (17) with SRM without explicit knowledge of $p(\mathbf{x}|\mathbf{z})$.

3.1 Deterioration modeling

Deterioration is modeled at the structural component level, since probabilistic physics-based deterioration models are mainly available at this level. The relation between the deterioration state $\mathbf{D}_{i,j}$ of component i at time t_j and the stochastic deterioration model parameters (which are here included in $\mathbf{X}_R$) can be written in generic form as:

$$\mathbf{D}_{i,j} = h_{D,i}(\mathbf{X}_R, t_j) \tag{18}$$

Deterioration increases with time t_j, which implies that the structural capacity $R(\mathbf{X}_R, t_j)$ decreases with t_j. Therefore, deterioration reduces, as expected, the reliability of structural systems.

It is also important to realize that deterioration of different components in a structural system is dependent due to spatial variability and uncertain common influencing factors such as environmental conditions, production quality and material properties (e.g. Vrouwenvelder 2004). This dependence reduces the reliability of redundant structural systems and implies that an inspection of the condition of one component also provides information on the condition of other components. Stochastic dependence can be modeled by introducing correlations among the stochastic parameters of the models describing the deterioration state of the different components. For this purpose, hierarchical and random field models are commonly applied (e.g. Ying and Vrouwenvelder 2007; Maes et al. 2008).

3.2 Repair modeling

Deteriorating components of a structural system can be repaired during the structure's service life. In general, the deterioration state $\mathbf{D}_{i,j}$ of any component i at time $t_j > t_k$, which is repaired in the interval $(t_{k-1}, t_k]$, can be described by the same deterioration model $h_{D,i}$ but with a new starting time, i.e. $\mathbf{D}_{i,j} = h_{D,i}(\mathbf{X}_R, t_j - t_k)$. The stochastic parameters influencing deterioration of the repaired component are modeled by new random variables, which are jointly included in $\mathbf{X}_R$. The dependence among the random variables representing the deterioration model parameters before and after repair is modeled by introducing additional correlations. In some cases, the model describing deterioration before a repair is replaced by a new model describing the deterioration after the repair. This could, for example, be necessary if the fatigue behavior of a component changes after a repair.

4 NUMERICAL EXAMPLE

The effect of different repair models is studied through a numerical example considering the steel frame shown in Figure 1. It has a service life of 20 years and consists of welded tubular steel members similar to a jacket support structure of an offshore wind turbine. The frame is subject to gravity and a time-varying lateral load, which is modeled by its annual maximum $S_{max,j}$. In addition, the frame is subject to high-cycle fatigue at selected welded connections – the fatigue hotspots – indicated as red dots in Figure 1. The evolution of the size of the fatigue cracks at each hotspot is described by a fatigue crack growth model based on Paris' law. The stochastic parameters of the model at each hotspot are the initial crack depth A_0, the material parameter C, the scale parameter of the hotspot stress range distribution K and the model uncertainties $B_{\Delta S}$ and B_{SIF}. The frame's braces are modeled as being either in a functioning or not functioning state in function of the size of the fatigue crack at the hotspots. The structural capacity of the damaged frame with respect to the applied load is determined by pushover analyses based on a non-linear finite element model. Details of the fatigue, structural performance and inspection model, and the computational methods employed in this example are documented in (Schneider et al. 2017; Schneider et al. 2018).

The parameterized rules that prescribe the actions in each year of the frame's service life in function of the available inspection data and past repairs considered in this example are as follows (Bismut et al. 2017; Luque and Straub 2019):

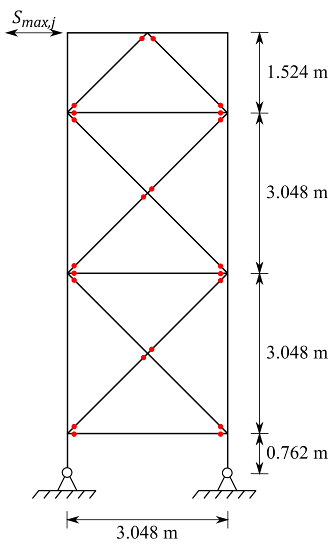

Figure 1. Steel frame. Red dots indicate fatigue hotspots.

1. Inspection campaigns are performed at fixed intervals Δt.
2. An additional inspection campaign is launched if the annual system failure probability exceeds a threshold p_{th}.
3. n_I hotspots are inspected during each inspection campaign.
4. The hotspots are prioritized for inspection according to an index proposed by Bismut et al. (2017), which is a function of a parameter η, the structural importance and fatigue reliability.
5. A weld is repaired if a fatigue crack is indicated and measured to be deeper than a_R.

Thus, the heuristic parameters defining the strategy $\mathcal{S}_{\boldsymbol{\theta}}$ are $\boldsymbol{\theta} = [\Delta t, p_{th}, n_I, \eta, a_R]^T$. The optimal parameters $\boldsymbol{\theta}^*$ are determined through an exhaustive search among the following sets of parameter values: $\Delta t \in \{4,8\}$ [year], $p_{th} \in \{5 \cdot 10^{-4}, 10^{-3}\}$, $n_I \in \{1, \dots, 22\}$, $\eta = 1$ and $a_R = 1$ [mm]. For each state of $\boldsymbol{\theta}$, $\mathbb{E}_{\mathbf{Z}}[C_T(\mathcal{S}_{\boldsymbol{\theta}}, \mathbf{Z})]$ is approximated using MCS with 200 samples of inspection data $\mathbf{Z}$ and corresponding repairs. The optimization considers the following parameter values for the cost model: $c_C = 1$, $c_I = 0.1$, $c_R = 0.3$, $c_F = 10^3$ and $r = 0.02$.

A welded connection with a fatigue crack can, for example, be repaired by grinding and subsequent filling of the groove by welding (e.g. Rodríguez-Sánchez et al. 2011). In the following, such a repair is model by two different models:

1. Perfect repair: A repaired welded connection will not fail due to fatigue.
2. Imperfect repair: The fatigue behavior of a repaired welded connection is described by the same crack growth model but with a new starting time. A new initial crack depth A_0' and material parameter C' are introduced to characterize the repair. The new parameters are independent of all other deterioration model parameters and have the same marginal prior distributions as the original initial crack depth A_0 and material parameter C.

The estimated expected service life cost $\mathbb{E}_{\mathbf{Z}}[C_T(\mathcal{S}_{\boldsymbol{\theta}}, \mathbf{Z})]$ in function of $\boldsymbol{\theta}$ are shown in Figure 2. In both cases, the optimal strategy $\mathcal{S}_{\boldsymbol{\theta}^*}$ in characterized by $\boldsymbol{\theta}^* = [\Delta t = 8, p_{th} = 10^{-3}, n_I = 7, \eta = 1, a_R = 1]^T$. The associated expected service life cost is $\mathbb{E}[C_T(\mathcal{S}_{\boldsymbol{\theta}^*})] = 4.9$.

5 CONCLUDING REMARKS

Risk-based optimization of inspection and repair strategies for deteriorating structural systems depends on the availability of (a) deterioration and structural performance models, (b) inspection

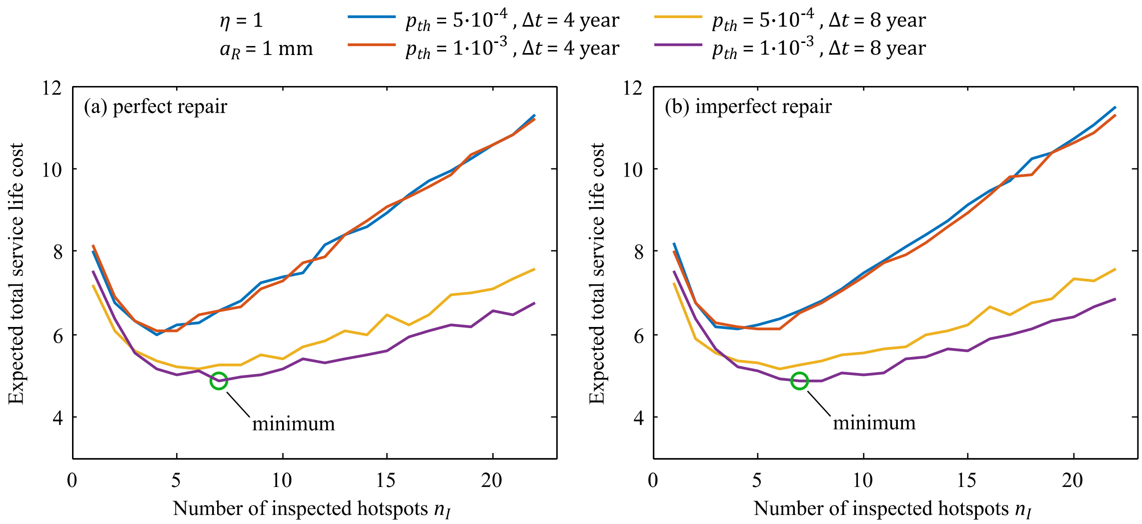

Figure 2. Expected total service life cost $\mathbb{E}_{\mathbf{Z}}[C_T(\mathcal{S}_{\boldsymbol{\theta}}, \mathbf{Z})]$ in function of $\boldsymbol{\theta} = [\Delta t, p_{th}, n_I, \eta, a_R]^T$. Case (a) perfect repair. Case (b) imperfect repair.

models, (c) repair models, (d) cost models and (e) robust and efficient computational strategies. The computational strategy applied in this paper is based on a direct policy search and was originally proposed by Luque and Straub (2019). The main objective of this paper is to study the influence of repair models on the results of a risk-based optimization of inspection and repair strategies. To this end, a numerical study is performed considering a steel frame with similar properties as a jacket support structure of an offshore wind turbine. The frame is subject to high-cycle fatigue. The example indicates that explicit modeling of fatigue failure following a repair has only a minor effect on the results. This is because the fatigue reliability of the welded connections is high (this is typically the case for steel support structures of offshore wind turbines) and thus the probability of repair is small. It follows that for the purpose of planning inspections and repairs of steel structures subject to fatigue a detailed modeling of the behavior of repaired welded connections is not required. This confirms similar findings by Straub (2014) who considered different repair models in the computation of the value of information of inspections of an individual welded connection.

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