Life-Cycle of Structures and Infrastructure Systems – Biondini & Frangopol (Eds)
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Life-cycle management of offshore wind deteriorating structures under ship collision accidental events

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ABSTRACT: In conventional industrial practices, the structural performance is evaluated against deterioration mechanisms as well as extreme and/or accidental events. However, most existing approaches treat the aforementioned structural assessments separately. In this work, we identify system inspection and maintenance strategies by jointly modeling deterioration processes and accidental/extreme events within the overall life-cycle management optimization. In particular, the decision-making objective is formulated considering a system failure risk metric that depends on the damage caused by deterioration processes and accidental/extreme hazards. In order to enable efficient inference and uncertainty propagation, we propose an underlying probabilistic approach relying on dynamic Bayesian networks. The efficacy of the proposed approach is tested in a life-cycle management setting where the risk of an offshore wind frame substructure is controlled by timely allocating inspection and maintenance actions. Within the investigation, we also observe the influence of ship collision events frequency on the resulting asset management strategies.

1 INTRODUCTION

Civil and maritime infrastructures support societal development and are essential for economic growth. Among them, offshore wind turbines offer a sustainable solution towards the pursuit of achieving renewable energy generation. Engineering systems are, however, exposed to deterioration mechanisms throughout their service life along with occasional extreme and/or accidental events, thus inducing a risk of structural failure. There is a need, therefore, for life-cycle management capable of controlling structural failure risks while minimizing inspection and maintenance costs. Driven by modern data collection techniques, the development of decision-making methods has been intensified in the last decade (Frangopol & Soliman 2016). From a computational standpoint, the identification of life-cycle management strategies involves the solution of a challenging decision-making problem under uncertainty and imperfect information, in which the uncertainties associated with the estimation of deterioration processes and data collection systems should also be adequately quantified.

Early risk-based approaches frame the decision-making problem in a simplified decision tree, where inspections and maintenance decisions are selected based on static pre-defined heuristic rules, e.g. equidistant inspection intervals, and repairs undertaken following damage indications. Later on, heuristic-based methods are integrated with dynamic Bayesian networks (DBNs) via policy search simulations, thus providing more flexibility to the definition of the heuristic decision rules (Luque & Straub 2019). Heuristic-based policies are, however, limited by the fact that only a subset of the vast policy space is explored. Addressing this limitation, decision-making methods relying on Markov Decision Processes (MDPs) and Partially Observable MDPs (POMDPs) have been proven to provide optimal policies in high-dimensional space settings (Papakonstantinou & Shinozuka 2014, Morato et al. 2022a). In very high dimensional state, action, and observation spaces, normally characteristic of engineering systems planning problems, schemes integrating POMDP with deep reinforcement learning can efficiently identify optimal policies, resulting in substantial cost savings compared

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to other heuristic-based and conventional management strategies (Andriotis & Papakonstantinou 2019, Morato et al. 2022b). The previously mentioned decision-making methods are usually applied so as to identify management strategies for deteriorating engineering components or systems. Yet, along with deterioration processes, engineering infrastructures are also occasionally exposed to extreme and/or accidental hazards. With respect to the latter, methods able to identify management strategies for engineering systems under extreme events have also been explored in the literature (Kumar et al. 2009). The severity and occurrence of extreme hazards are normally characterized as low-probability high-consequence events, (Stewart & Rosowsky 2022). In that case, the goal of adequate strategies generally involves controlling the vulnerability of affected structural systems, as well as mitigating human, social, environmental, and economic losses. However, high-probability low-consequence accidental events can also occur, and while they may be associated with less critical consequences, the structural reliability of the concerned engineering systems can be severely compromised. For example, offshore wind structures are exposed to multiple hazards throughout their lifetime, including extreme environmental loads and accidents, e.g. ship collisions. In conjunction with deterioration processes, damage due to high-probability low-consequence ship collisions detrimentally affects the capacity of offshore wind structural systems, rendering them potentially unable to withstand future hazards.

Most reported planning methods and conventional industrial practices deal with engineering systems exposed to either deterioration mechanisms or extreme events. In this work, we propose a probabilistic modeling framework based on dynamic Bayesian networks jointly treating deterioration processes and accidental/extreme events. Particularly, the system's structural reliability is formulated conditional on its components' reliability, whose evolution is modeled considering both probabilistic deterioration processes and accidental/extreme events. The proposed scheme constitutes the underlying probabilistic foundation, which integrated with heuristic- or POMDP- based decision-making methods, is able to provide management strategies for deteriorating engineering systems under accidental and/or extreme events. To test our approach, life-cycle management heuristic-based policies are identified for a structural system subject to fatigue deterioration and accidental ship collision events, also investigating the effect of accidental events occurrence and their intensity on the resulting strategies.

2 LIFE-CYCLE MANAGEMENT OF DETERIORATING STRUCTURES UNDER ACCIDENTAL AND/OR EXTREME EVENTS

In this section, we propose a probabilistic modeling approach based on dynamic Bayesian networks for the estimation and inference of the reliability of a structural system subject to both time-varying deterioration processes and accidental/extreme loads. Relying on computed system reliability metrics, along with inspection and maintenance costs, life-cycle management policies can then be identified via policy search simulations or Markov decision processes.

2.1 *Probabilistic modeling via dynamic Bayesian networks*

Encoding the conditional relationships among random variables, Bayesian networks are acyclic graphical models that enable robust inference based on observed information. Bayesian networks that track dependencies over time are commonly denoted temporal template models, or more generally, dynamic Bayesian networks (DBNs). By leveraging the inference capabilities featured by DBNs, the reliability of a structural system can be efficiently estimated. The overarching scheme for probabilistically modeling the reliability of a deteriorating structural system under accidental/extreme events over time is graphically shown in Figure 1. Chance nodes represent random variables and are bounded by circular edges in the graph, additionally filled with grey color if they are partially observable. Also, network template models are enclosed by a blue or green box, indicating whether they are repeated over components or intensity measures, respectively.

2.2 *Stochastic deterioration processes*

The damage condition state caused by a non-stationary deterioration process, e.g. fatigue or corrosion, can be updated over time based on collected information through a two-step

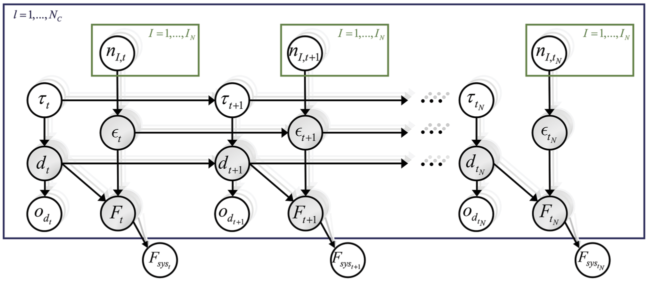


Figure 1. Overarching graphical representation of the proposed probabilistic approach. Damage evolution caused by both deterioration processes and accidental/extreme events is modeled over time through dynamic Bayesian networks. Each component's reliability is conditional on deterioration and accidental/extreme damage, whereas the system's reliability depends on the components' reliability.

process. Firstly, the joint state comprised of the damage condition, d_t, and the deterioration rate, τ_t while conditional on past observations, $\boldsymbol{o_0}, \ldots, \boldsymbol{o_t}$, advances over time according to the transition model $p(d_{t+1}, \tau_{t+1} | d_t, \tau_t)$, as:

$$p(d_{t+1}, \tau_{t+1} | \boldsymbol{o_0}, \ldots, \boldsymbol{o_t}) = \sum_{d_t} \sum_{\tau_t} p(d_{t+1}, \tau_{t+1} | d_t, \tau_t)\, p(d_t, \tau_t | \boldsymbol{o_0}, \ldots, \boldsymbol{o_t}) \tag{1}$$

Based on the information collected from inspections or monitoring, the damage is then updated by applying Bayes' rule. The likelihood $p(\boldsymbol{o_{t+1}} | d_{t+1})$ can be directly defined from probability of detection curves or other observation uncertainty measures:

$$p(d_{t+1}, \tau_{t+1} | \boldsymbol{o_0}, \ldots, \boldsymbol{o_{t+1}}) \propto p(\boldsymbol{o_{t+1}} | d_{t+1}) p(d_{t+1}, \tau_{t+1} | \boldsymbol{o_0}, \ldots, \boldsymbol{o_t}) \tag{2}$$

2.3 *Accidental and/or extreme events*

Occasional accidental or extreme events can be categorized according to their severity and can be probabilistically modeled based on their occurrence rate. The frequency associated with an accidental event depends on the operational conditions, location, and specific characteristics of the structural system. Based on the specific frequency, annual event occurrences can be estimated, for example, through a Poisson random process. In Figure 1, the annual occurrence is depicted with the node n_I for each considered intensity measure, I, and graphically represented as a template model. The damage sustained due to accidental or extreme events, ε, can be then modeled conditional on annual event occurrence. In terms of reliability, a component or system limit state can be defined based on the structural damage, ε, and a case-dependent safety measure.

2.4 *System structural reliability*

At the system level, the failure event can be defined conditional on the component's failure probability, represented in Figure 1 with nodes F_{sys} and F, respectively (Morato et al. 2022b). And, as mentioned previously, the failure probability associated with each component depends, in turn, on the deterioration, d, and accidental, ε, damage condition.

2.5 *Reliability-based robustness index*

Along with reliability measures, quantifying the resistance of a structural system against accidental or extreme loads can also be informative for life-cycle management considerations. As explained by Biondini (2009), structural robustness can be measured by comparing the structural performance (e.g. reliability) of the system in a damaged state with respect to the system in an intact condition. A reliability-based robustness index, I_R, can be therefore formulated as (Frangopol & Curley 1987):

$$I_R = \frac{\beta_{sys,0}}{\beta_{sys,0} - \beta_{sys,d}} \tag{3}$$

where $\beta_{sys,0}$ and $\beta_{sys,d}$ correspond to the reliability index (i.e. $\beta_{sys} = -\Phi^{-1}\left[p_{F_{sys}}\right]$) estimated for the intact and damaged system, respectively.

2.6 *Life-cycle management planning*

As mentioned in Section 1, life-cycle strategies can be identified through heuristic-based policy search or via POMDP-based deep reinforcement learning, potentially including additional maintenance actions undertaken in response to damage caused by accidental or extreme events. In any case, the objective of the life-cycle management decision problem is stated as the minimization of the total expected cost, $\mathbf{E}[c_T]$:

$$\boldsymbol{E}[c_T] = \boldsymbol{E}\left[\sum_{t=0}^{t_N}\left[\gamma^t\left(c_{I,t} + c_{R,t} + r_{F,t}\right)\right]\right] \tag{4}$$

where c_I and c_R, stand for inspection and repair costs, respectively; while the system risk, r_F, is defined as the system failure probability, pF_{sys}, multiplied by the failure cost, c_F. Note that the total cost is discounted by the factor γ. By identifying policies on the basis of the aforementioned optimization objective, life-cycle management policies are able to jointly consider the risk induced by deterioration processes and occasional accidental/extreme events, both of them encapsulated in the system risk metric, r_F.

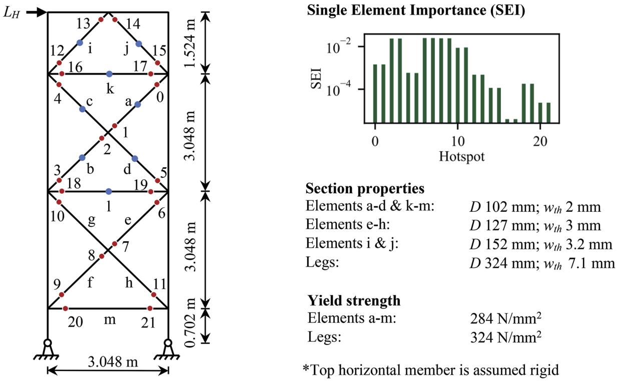
3 LIFE-CYCLE MANAGEMENT PLANNING FOR A DETERIORATING OFFSHORE WIND SUBSTRUCTURE SUBJECT TO SHIP COLLISIONS

The main goal of this study is to determine the influence of occasional accidental events on life-cycle management strategies. Specifically, life-cycle management policies are identified for a structural system subject to both fatigue deterioration and accidental ship collision events. A heuristic-based policy search is conducted in order to identify life-cycle strategies, evaluating each considered heuristic combination over 2,000 policy realizations on a 30-year decision horizon. In particular, a specified number of braces (and their corresponding fatigue hotspots) are inspected at equidistant inspection intervals, prioritized according to their brace failure probability. Besides, a brace is subsequently repaired if a crack is observed or once the brace failure probability exceeds 10^{-3}. The heuristic-based policy becomes the optimized heuristic combination that results in the minimum total life-cycle cost, among all evaluated heuristic rules. The inspection and repair costs are specified for each element as c_I = 0.4 and c_R = 30 monetary units, whereas the system failure cost is defined as c_F = 50,000 monetary units. Also, a discount factor is specified as γ = 0.95. Note that more optimal policies can be found via POMDP-based deep reinforcement learning approaches. As mentioned earlier, the primary aim of the study is not reaching policy optimality but observing the effect of considering both deterioration processes and extreme/accidental events on the retrieved life-cycle strategies.

3.1 *Case study description*

3.1.1 *System structural reliability*

The methodology proposed in Section 2 is tested for a typical engineering system in the structural reliability community, the Zayas frame, considered in this work as a 2-dimensional representation of an offshore wind substructure. The frame features 2 legs and 13 braces, with the characteristics shown in Figure 2. The failure of the system corresponds to the event in which the frame is not able to withstand a concentrated horizontal load applied at the upper-left corner, i.e. the probability of the external horizontal load exceeding the structural system resistance $p_r[L_H > L_{push}]$. The horizontal load is characterized as a lognormal random variable with mean $\mu_{L_H} = 70$ kN and 25% coefficient of variation, while the system resistance is assumed deterministic. The system failure depends on the event of a potential brace failure, caused by fatigue deterioration and/or accidental collision damage. Particularly, a brace failure event is defined as a series system including one/two fatigue hotspots and a collision failure event, each of them estimated based on the limit states explained hereafter. To define the failure probability of the frame, pF_{sys}, conditional on all brace failure/survival state combinations, 8,192 (= 2^{13}) non-linear static push-over simulations have been run with the assistance of the computer code 'USFOS'. For a complete description of the frame structural reliability computation, the reader is referred to Morato et al. (2022b).



Section properties
Elements a-d & k-m: D 102 mm; w_{th} 2 mm
Elements e-h: D 127 mm; w_{th} 3 mm
Elements i & j: D 152 mm; w_{th} 3.2 mm
Legs: D 324 mm; w_{th} 7.1 mm

Yield strength
Elements a-m: 284 N/mm²
Legs: 324 N/mm²

*Top horizontal member is assumed rigid

Figure 2. Zayas frame geometry and material properties, adapted from Morato et al. (2022b).

3.1.2 *Fatigue deterioration*

The deterioration condition of each fatigue hotspot is here described according to the Markovian model, originally proposed in Ditlevsen & Madsen (2007):

$$d_{t+1} = \left[\left(1 - \frac{m}{2}\right) C_{FM} S_R^m \pi^{m/2} n + d_t^{1-m/2}\right]^{2/2-m} \tag{5}$$

where the evolution over time, t, of the crack depth, d, is formulated through a fracture mechanics law with material parameters $ln(C_{FM}) \sim \mathcal{N}(\mu = -35.2, \sigma = 0.5)$ and $m = 3.5$, stress range $S_R \sim \mathcal{N}(\mu = 70, \sigma = 10)\ N/mm^2$, $n = 10^6$ annual stress cycles, and initial crack depth $d_0 \sim Exp(\mu = 1)$ mm. At the hotspot level, fatigue failure p_{F_t} occurs once the crack depth, d, exceeds a critical size, $d_c = 20\ mm$, formally defined as $p_{F_t} = Pr[g_t \leq 0]$ and computed via a through-thickness failure criterion (Hlaing et al. 2022), i.e. $g_t = d_c - d_t$. Adopting the probabilistic methodology proposed in Section 2, the fatigue deterioration is encoded in a deterioration rate DBN model. The continuous crack depth, d, is adequately discretizated into states conditional on $|\mathcal{S}_\tau| = 31$ fully observable deterioration rate states. In terms of the observational model, the inspection quality is quantified with a Probability of Detection curve $PoD(d) \sim Exp(\mu = 8)$. More details can be found in Morato et al. (2022a).

3.1.3 *Ship collisions*

The accidental event is defined as a ship bow impact on the midpoint of a brace and its damage is estimated by means of the absorbed energy. For the purpose of this study, only elements on the 'splash zone' are potentially subject to ship collisions, i.e. brace elements a-d and i-l. The mechanisms for energy absorption are assumed as plastic bending and plastic tensile strain. Local denting and global deflection of the installation, as well as local deformation of the vessel, are not accounted for. To determine the energy absorbed by the collided structure, a ship bow collision on a brace member is considered as a three-point centrally loaded beam bending problem, (Zhang et al. 2019). The maximum capacity of energy absorbed by bending and tension, $\in_{max}$, corresponds then to the hinge rotation limit of the element, formulated as:

$$\in_{max} = 4\sigma_y w_{th}(D - w_{th})^2 \alpha \left(\frac{w_{th}}{D}\right)^{\beta} + \pi\sigma_y w_{th}(D - w_{th})\frac{L}{2}\left[\alpha\left(\frac{w_{th}}{D}\right)^{\beta}\right]^2 \tag{6}$$

where w_{th}, D, and L represent the wall thickness, outer diameter, and length of each tubular member, respectively, while σ_y corresponds to the yield strength. According to Marshall et al. (1977), a lower and upper bound solution can be specified for the plastic hinge rotation at failure for a tubular element, where the range for the multiplicative constant α may be defined between 122 and 12,800 and the exponent β may take values between 2.5 and 3. To account for the uncertainty associated with the previously mentioned parameters and defined for each considered element thickness and diameter, α is described as a uniform random variable, $\alpha \sim \mathcal{U}(122, 12800)$, and β is assumed as a Gaussian random variable, $\beta \sim \mathcal{N}(\mu = 2.75, \sigma = 0.25)$. Geometrical and material properties are treated here as deterministic variables.

Table 1. Occurrence frequency statistical description of all examined accident ship collision events, categorized according to their intensity measure (collision energy).

Occurrence frequency/intensity	0.625 kJ	3.125 kJ	6.250 kJ	9.375 kJ	12.5 kJ
Low (λ_{low})	10^{-2}	10^{-3}	$5 \cdot 10^{-4}$	10^{-5}	10^{-6}
Medium (λ_{medium})	$5 \cdot 10^{-2}$	$5 \cdot 10^{-3}$	10^{-3}	$5 \cdot 10^{-5}$	$5 \cdot 10^{-6}$
High (λ_{high})	10^{-1}	10^{-2}	$5 \cdot 10^{-3}$	10^{-4}	10^{-5}

During the computation of policy evaluations, the failure probability of an accidental event is estimated, at each time step, according to the limit state, $g_{col} = \in_{max} - \in_{col}$, with $\in_{max}$ calculated following Equation 6. In terms of the collision energy, $\in_{col}$, which can be linked to the intensity measure of an accidental event, a set of collision intensities are here investigated ranging between 0.625 and 12.5 kJ. The intensities can be regarded as reasonable collision scenarios for the Zayas frame, corresponding specifically to a ship mass between 5 and 100 tonnes colliding at 0.5 m/s. In the numerical experiments, three collision occurrence event settings are tested, representative of low, medium, and high frequencies, all of them described as Poisson processes. Table 1 lists the mean annual frequency, λ, considered for each analyzed setting. While evaluating life-cycle policies, the number of ship collision events, $n_{I,col}$, is sampled at each time step, thereby enabling the computation of the collision energy $\in_{col}$ and the accidental event failure probability.

3.2 *Results and discussion*

3.2.1 *Robustness analysis*

To better understand the ability of the analyzed frame to withstand potential ship collisions, the robustness of each brace is quantified according to Equation 3 and displayed in Figure 3. The intact reliability index, β_0, corresponds to the case in which only deterioration damage is considered, whereas the damaged reliability index, β_d, also accounts for accidental events associated with a certain collision intensity, along with fatigue deterioration. As expected, more severe ship collisions lead to an overall robustness reduction, also accentuated by longer fatigue deterioration exposure. Interestingly, the observed robustness indices are clearly influenced by each brace's structural importance, defined according to Morato et al. (2022b).

3.2.2 *Life-cycle costs and policies*

The total expected cost, $\mathbf{E}[c_T]$, resulting from all examined accidental event frequency settings is reported in Table 2, also listing the corresponding expected inspection and repair costs along with the system failure risk, i.e. $\mathbf{E}[c_I]$, $\mathbf{E}[c_R]$, and $\mathbf{E}[r_F]$. Whereas more intense ship collision events naturally lead to higher life-cycle total expected costs, expected inspection and repair costs are also clearly influenced by the intensity of accidental events. Considering only

Table 2. Expected total cost resulting from the conducted numerical experiments for settings with varying frequency of collision event occurrence.

Occurrence frequency	E[c_I](% E[c_T])	E[c_R](% E[c_T])	E[r_F](% E[c_T])	E[c_T](95% C.I.)
Zero (λ_{zero})	15.31 (7.3 %)	55.99 (26.8 %)	137.35 (65.9 %)	208.65 (±0.01)
Low (λ_{low})	15.29 (7.0 %)	59.75 (27.2 %)	144.41 (65.8 %)	219.45 (±0.02)
Medium(λ_{medium})	11.99 (4.5 %)	66.01 (25.1 %)	185.08 (70.4 %)	263.08 (±0.04)
High (λ_{high})	11.01 (3.4 %)	86.02 (26.5 %)	227.59 (70.1 %)	324.63 (±0.05)

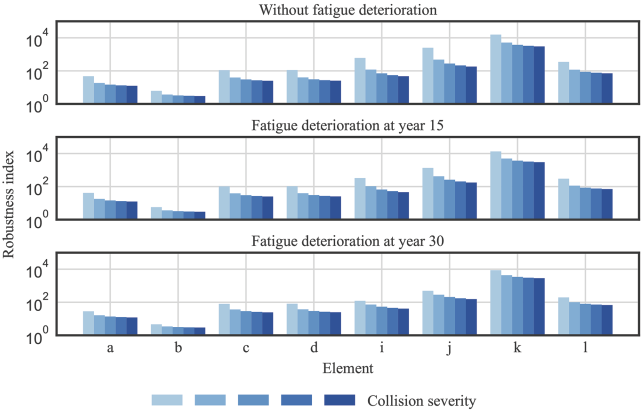


Figure 3. Reliability-based robustness index estimated for all Zayas' brace elements potentially subject to ship collision accidental events (darker colors represent major severity).

fatigue deterioration during the planning stage would have resulted in a higher failure risk for more severe collision scenarios, with negligible influence on inspection and repairs. To further investigate the effect of collision occurrence on the retrieved policies, an additional analysis is conducted comparing the heuristic decision rules evaluated for each occurrence setting against the baseline case, in which only fatigue deterioration is considered. The normalized difference between the $\mathbf{E}[c_T]$ resulting from each evaluated heuristic rule combination h_i and the optimized heuristic-based policy h_{opt} is defined as the comparative proxy, formulated as:

$$\overline{h_i} = \frac{\mathbf{E}[c_T(h_i)] - \mathbf{E}\left[c_T\left(h_{opt}\right)\right]}{\mathbf{E}\left[c_T\left(h_{opt}\right)\right]} \tag{7}$$

The above-mentioned metric, $\overline{h_i}$, is compared in Figure 4 for three ship collision frequency settings (i.e. λ_{low}, λ_{medium}, λ_{high}) against the case where only fatigue deterioration is modeled, λ_{zero}. Additionally, optimized heuristic-based policies are marked with a plus marker for each considered collision event occurrence case and a circular marker for λ_{zero}. As seen in the figure, the optimized heuristic-based policy remains the same for λ_{low} setting, yet it is clearly different for the other two cases λ_{middle} and λ_{high}. As one could expect, the life-cycle policy is mainly driven by fatigue deterioration when the frequency of accidental events is very low. Nevertheless, life-cycle management strategies are influenced by both fatigue deterioration and ship collision for the other two examined ship collision frequency scenarios. Additionally, it can also be observed that the optimized heuristic-based policy for λ_{zero} setting is farther from the optimized life-cycle policy when considering higher frequency of ship collisions, thus demonstrating the importance of jointly modeling both fatigue deterioration and accidental events.

4 CONCLUSIONS

This study reveals the importance of accounting for the increased risk caused by accidental events in life-cycle management planning for deteriorating structural systems. In the numerical

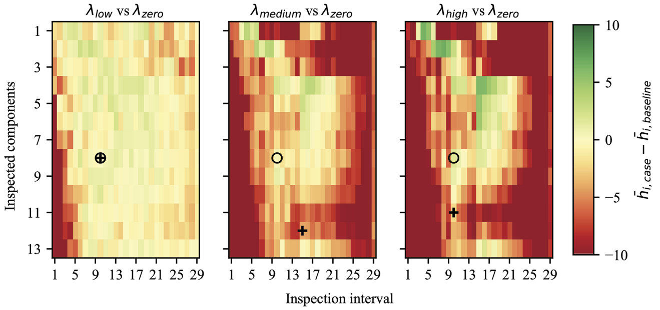


Figure 4. Heatmap representation of the difference between the normalized expected total costs resulting from settings with varying frequency of ship accidental collision events and the baseline case, in which only fatigue deterioration is accounted for.

experiments, heuristic-based life-cycle management policies are identified for an offshore wind substructure subject to fatigue deterioration and ship collisions, and the results indicate that the retrieved strategies are highly sensitive to the intensity and occurrence frequency of the examined ship collision events. In terms of decision-making, further research efforts might explore the integration of the proposed probabilistic approach with deep reinforcement learning methods.

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