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A decision support framework for fatigue assessment of steel bridges

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ABSTRACT

Many bridges are approaching or have already passed their expected service life. For steel bridges, fatigue is often the decisive degradation phenomenon that theoretically puts restrictions on a continued use. At the same time, fatigue is also afflicted with large uncertainties on the resistance side as well as on the action effect side. An accurate assessment of the service life will require measures outside the governing regulations but understanding what steps to take and how to consider the outcome for decisions on interventions can be a difficult task for a non-expert. This paper presents possible assessment actions and a decision support framework for rational decisions on interventions to extend the theoretical service life of existing bridges. A case study of a critical railway bridge is incorporated to demonstrate the framework. The aim is to provide a tool for bridge managers on how to evaluate and procure different assessment actions.

1. Introduction

There is an ever growing need to make decisions on interventions to keep existing bridges in service. Several investigations have shown that most countries with a developed transport infrastructure are facing challenges with a growing number of bridges approaching their expected service life [1, 2]. These bridges cannot be upgraded or replaced within reasonable budget restraints and, for sustainability reasons, their service life should be extended as far as possible. This will require the use of sophisticated methods for assessment and service life prediction. Guidelines can be found in, e.g., [1] and [3], where different assessment levels are suggested ranging from a conventional assessment following the regulations to advanced methods using fracture mechanics and probabilistic evaluation. Both publications suggest a consecutive approach with a stepwise increase of complexity and sophistication. This development of the assessment model will presumably increase the ability to predict a more realistic structural behaviour. On the other hand, models describing more complex phenomena will typically require more input variables and modelling choices afflicted with uncertainty. This leads to a greater need for reliable information concerning the properties and actual condition of the structure.

As an alternative to a consecutive assessment approach, a framework for classification of assessment actions and decision support has been suggested by Björnsson et al. [4]. The attributes of assessment actions are visualized as a cube in Fig. 1 hereafter called the MUK approach. This model allows a distinction between the contributions of different actions in connection with the prediction accuracy. The first attribute of the MUK approach is defined as the modelling sophistication (M), which measures how detailed the theoretical model for condition assessment is. The second factor represents the uncertainty consideration (U), that is how the uncertainties of the assessment are considered. The third factor represents the knowledge content (K), considering how information

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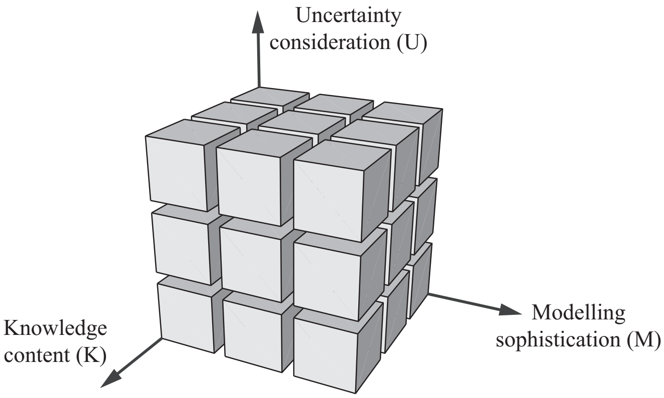


Fig. 1. A model for classification of assessment actions (MUK approach).

about the structure have been acquired and used in the assessment. The three attributes of the MUK approach can be visualized as a cube with each axis corresponding to one of the attributes; see Fig. 1. An assessment can be improved by proceeding along one axis but preferably by progressing in a three-dimensional sense along all axes. The origin of the cube can be interpreted as a preliminary assessment in accordance with the regulations. Moving away from the origin is expected to give an improved accuracy of results but, it also entails more complex methods requiring a greater number of variables [4]. The different attributes and levels of the MUK approach are explained in more detail in Section 2 considering fatigue assessments.

If a preliminary assessment indicates an exhausted service life, the bridge manager has to decide on more exhaustive assessment actions or possible interventions such as repair, rehabilitation, and demolition, to reduce the danger with respect to public safety [5]. The MUK approach combined with Bayesian decision theory under uncertainty is suggested as a tool to aid the decision maker in this navigation. It enables a rational consideration of uncertainties of the input variables and an evaluation of decision alternatives by minimizing expected costs or other negative consequences. An approach using influence diagrams, a Bayesian network augmented with decision and utility nodes [6], as suggested in [4] is implemented in this study. An influence diagram allows an evaluation of expected utilities of different decision options based on the information known at the time of the decision. The decision model is explained in Section 3.

The use of influence diagrams for decision support is suggested also in [7] and [8] where the deterioration of offshore structures is treated. These studies are focused on optimal planning of operation and maintenance (O&M) actions, which for offshore structures can constitute a significant part of the total life cycle cost [9]. For bridges, the relation between maintenance costs and consequences of failure is typically different. A considerable service life, up to 100 years or more, and large consequences of failure necessitate robust designs and low probabilities of failure. Actions to ascertain the resistance of a deteriorating bridge must be taken before obvious damages emerge. Hence, this study is focused on assessment actions rather than on O&M strategies. The purpose is to support rational decisions on procurement of measures to improve the accuracy of the predicted service life, with an overall aim to extend the service life of existing bridges.

The application of the MUK approach and the decision framework for fatigue assessment of existing steel bridges is elaborated in this paper. First, available methods for fatigue assessment are reviewed and a classification according to the model in Fig. 1 is suggested. Secondly, the decision model based on an influence diagram is described. Finally, a case study of a steel bridge subjected to fatigue deterioration is presented to demonstrate the approach.

2. Fatigue assessment

The assessment of an existing bridge considering fatigue is typically performed using the same methods as for the design of new bridges. Simplified characteristic load models are used and the verification is performed using a deterministic safety format. This is denominated as *Phase I: Preliminary evaluation* in [3]. Different attributes to consider in subsequent more detailed assessments can be classified according to Fig. 1. The three attributes; model sophistication (M), uncertainty consideration (U), and knowledge content (K), are described considering fatigue assessment in the following sections.

2.1. Model sophistication

For a condition assessment, a theoretical model to predict the structural behaviour due to loading is needed and, furthermore, a model reflecting the deterioration process. The model sophistication (M) is an attribute describing the complexity of the theoretical model, typically based on how many variables it contains and how accurately it reflects the performance of the bridge. However, increasing the level of complexity can be time-consuming, require additional data, introduce errors, etc. Therefore, the expected costs and benefits of moving to a higher level of sophistication should be evaluated and compared with options of moving along the other two axes in Fig. 1.

Considering fatigue, the accuracy of the service life prediction depends on the estimated load effect, described as a stress range spectrum, and how the endurance is estimated. A preliminary assessment according to the regulations can be formulated as a safety margin equivalent to the method suggested in, e.g., the Eurocode [10]

$$M_0 = \frac{\Delta\sigma_C}{\gamma_{Mf}} - \gamma_{Ff}\Delta\sigma_{E,2} \geq 0 \tag{1}$$

where $\Delta\sigma_C$ is the fatigue strength at 2 million cycles, γ_{Mf} is a partial safety factor for the fatigue strength, γ_{Ff} is a partial safety factor for the equivalent stress range, and $\Delta\sigma_{E,2}$ is an equivalent stress range representing the load effect. This verification format facilitates a practical assessment of the load bearing capacity. However, it is based on a conservative estimation of the load effect to one single value ($\Delta\sigma_{E,2}$) and a fatigue strength estimated from *S–N* curves determined from constant amplitude testing.

A model sophistication could include more detailed structural analyses to reach a better estimation of the stress state, e.g., by estimating the structural hot spot stress or the effective notch stress [11]. It is, however, not evident that these local reference stresses in general provide a better estimation of the fatigue life in comparison to a nominal stress approach [12]. Hence, the model sophistication in this paper is focused on the verification format. An increase in complexity in comparison to Eq. (1) is to use the Palmgren-Miner rule for linear damage accumulation. It entails a more accurate modelling of the load effect, allowing a consideration of a complete stress range spectrum caused by an elaborate description of the traffic loads. In this case the verification can be formulated as

$$M_1 = D - \sum_i \frac{n_i}{N_{Ri}} = D - \frac{1}{K_1}\sum_j n_j(\gamma_{Ff}\gamma_{Mf}\Delta\sigma_j)^{m_1} - \frac{1}{K_2}\sum_k n_k(\gamma_{Ff}\gamma_{Mf}\Delta\sigma_k)^{m_2} \geq 0 \tag{2}$$

which is valid for a bilinear *S–N* curve as suggested in [10]. In the calculation of the fatigue endurance, N_{Ri}, the fatigue strength is represented by K_1 and K_2 in Eq. (2) and the associated variables m_1 and m_2 describing the bilinear *S–N* curve. The load effect is considered by a stress range spectrum described by n_i cycles in stress range $\Delta\sigma_i$ and by n_k cycles in stress range $\Delta\sigma_k$ for the two branches of the *S–N* curve. A damage index of $D = 1$ is typically assigned as an indication of an exhausted fatigue life. The Palmgren-Miner rule allows a consideration of a mixture of different vehicles and variations of traffic intensity over time.

The linear accumulation of damage implied by the Palmgren-Miner rule is often criticized for its inability to reflect the pronounced nonlinear progression of fatigue damage [13]. This can be satisfied by increasing the modelling sophistication further by using linear elastic fracture mechanics (LEFM). A safety margin can be formulated as

$$M_2 = \int_{a_0}^{a_c}\left(\frac{da}{dN}\right)^{-1} da - N \geq 0 \tag{3}$$

where a_0 is the initial crack depth, a_c is the critical crack depth representing the final failure of the detail, da/dN is the crack growth rate, and N is the total number of accumulated cycles. An established formulation of the crack growth rate is the Paris law [14]

$$\frac{da}{dN} = A\,\Delta K(a)^m \tag{4}$$

where A and m are constants depending on material and the applied conditions, and ΔK is the stress intensity factor range (SIFR). A bilinear formulation of a crack growth law can be found in, e.g., the British standard BS 7910 [15]. For welded structures, the SIFR can be expressed as

$$\Delta K(a) = \Delta\sigma\sqrt{\pi a}\;Y(a)\,M_k(a) \tag{5}$$

where $Y(a)$ is a geometry correction factor considering the geometry of the unwelded component, and $M_k(a)$ is a stress magnification factor due to the weld geometry [16]. In a deterministic verification, the stress range $\Delta\sigma$ in Eq. (5) should be multiplied with appropriate partial safety factors.

2.2. Uncertainty consideration

A preliminary assessment is typically performed using a deterministic safety format with partial safety factors as represented by Eq. (1). An advancement along the *U* axis in Fig. 1 is to use a reliability-based assessment as suggested in, e.g., [17]. For fatigue assessment based on the Palmgren-Miner rule, a limit state equation can be formulated by adding uncertainty to the variables in Eq. (2)

$$g(\mathbf{x}, N) = \delta - \frac{1}{K_1}\sum_j n_j(C_S\Delta\sigma_j)^{m_1} - \frac{1}{K_2}\sum_k n_k(C_S\Delta\sigma_k)^{m_2} \tag{6}$$

where g depends on the basic random variables in the vector $\mathbf{x}$ and the accumulated number of cycles N, δ represents the accumulated damage when the fatigue life is exhausted and C_S is a model uncertainty factor related to the estimated stresses. A state of failure is defined by $g(\mathbf{x}, N) \leq 0$ and the probability of failure as

$$P_f = P[g(\mathbf{x}, N) \leq 0] \tag{7}$$

The reliability index is related to the probability of failure as $\beta = -\Phi^{-1}(P_f)$, where $\Phi^{-1}(\cdot)$ is the inverse of the standardized normal distribution function.

The corresponding limit state equation based on LEFM can be expressed as

$$g(\mathbf{x}, N) = N_c(\mathbf{x}) - N \tag{8}$$

where $N_c(\mathbf{x})$ represents the resistance as the number of cycles to failure and N is the total number of accumulated cycles. The former should be determined by integrating the crack growth rate. For variable amplitude loading, the integration can be performed using the expected crack growth rate [17]

$$E\left[\frac{da}{dN}\right] = A_a E[\Delta\sigma^{m_a}]_{\Delta\sigma_{th}}^{\Delta\sigma_{ab}} (C_S C_{SIF}\sqrt{\pi a}\,Y(a)M_k(a))^{m_a} + A_b E[\Delta\sigma^{m_b}]_{\Delta\sigma_{ab}}^{\infty} (C_S C_{SIF}\sqrt{\pi a}\,Y(a)M_k(a))^{m_b} \tag{9}$$

where $E[\cdot]$ denotes the expected value. The formulation is valid for a bilinear crack growth as suggested in [15] and [17]. The variables A_a, A_b, m_a, and m_b are material parameters dependent on the applied conditions. The stress range $\Delta\sigma_{ab}$ is the value corresponding to the intersection between the two branches, and $\Delta\sigma_{th}$ is the threshold stress range corresponding to the crack growth threshold K_{th}. A model uncertainty factor C_{SIF} has been added considering the uncertainty of the stress intensity factor. A more elaborate description of the limit state Eq. (9) can be found in [18].

The remaining service life should be assessed against a target reliability in the reliability-based format. In the standard ISO 13822 [5], target values of $\beta = 3.1$ and $\beta = 2.3$ are suggested for not inspectable and inspectable details, respectively. The target values are valid for a reference period of the intended remaining service life.

The next level along the U axis in Fig. 1 could be a risk-based assessment considering the consequences of a failure. Examples on applications can be found in, e.g., [19] and [20]. The focus is typically to optimize inspection and maintenance actions. The models for fatigue deterioration covered above are, however, also applicable for such analyses.

2.3. Knowledge content

A preliminary assessment is typically based on nominal dimensions and material properties stated on drawings produced for the construction. The manner with which additional information about the bridge is collected and incorporated in the assessment is graded along the third axis in Fig. 1 – knowledge content (K). The information could relate to, e.g., material properties, dimensions, actual loads, measured strains, and existing flaws and damage. How the additional information can affect the assessment depends on the level of model sophistication as well as the uncertainty consideration, the two other axes in the MUK approach.

The stress level has a decisive influence on the fatigue endurance. Hence, in-situ measurements of the strain history under actual traffic conditions is suggested as a possible advancement along the K axis. It has the potential of reducing the estimated load effect significantly in comparison to theoretical structural analyses using standardized load models. Measured strains recalculated to stresses can also be used in both deterministic and probabilistic verification formats. The use of measured strains for fatigue assessment of steel bridges has been treated in, e.g., [21, 22].

A probabilistic format based on LEFM allows a connection between a theoretical assessment and results from inspections. The inspection itself is, however, uncertain and this must be considered in the evaluation of the results. The updating of the probability of failure can be expressed as a conditional probability using Bayes' theorem [23]

$$P_f^U = P[g(\mathbf{x}) \le 0 | H_D(\mathbf{x}) \le 0] = \frac{P[g(\mathbf{x}) \le 0 \cap H_D(\mathbf{x}) \le 0]}{P[H_D(\mathbf{x}) \le 0]} \tag{10}$$

where $P_f{}^U$ is the updated probability of failure and $H_D(\mathbf{x})$ is a detection event that can be expressed as

$$H_D(\mathbf{x}) = a(\mathbf{x}, N_i) - a_d \tag{11}$$

where $a(\mathbf{x}, N_i)$ is the estimated crack depth at N_i cycles and a_d is the lower level detectability which is typically called the probability of detection (PoD).

Other possible actions to gain information include material testing of crack growth properties or fatigue testing of the fatigue endurance. These methods are, however, more invasive, requiring material samples and destructive testing.

3. Decision model

How to navigate in the MUK triplet and determine what assessment actions to engage should be based on rational decision making. As an example, it is logical for an engineer specialized in advanced structural modelling to advocate activities within his or her own field. But for a bridge manager, activities leading to the greatest utility, highest benefit, or lowest expected cost should be procured, even though it might involve engaging different specialists.

A decision model based on the influence diagram in Fig. 2 is suggested for the purpose of assessment of existing bridges. The ovals represent chance variables which in this case concern the actual state of the detail and the outcome of the assessment actions. The rectangles represent decision variables such as which assessment action to engage and possible repair actions. The utility variables are shown as diamonds and are in this case the costs of assessment actions and the costs depending on the random outcome, such as failure and repair. More detailed descriptions on the principles of influence diagrams can be found in, e.g., [6].

The aforementioned decision problem is solved by maximizing the expected utility. The model in Fig. 2 is composed of the decision variables e and r representing the assessment option and repair action, respectively. It also has two chance variables θ and z representing the natural state of the bridge or a single detail and the outcome of the assessment option, respectively. The repair action should be decided based on the outcome of the assessment which is unknown at the time of analysis. Therefore, a decision rule is

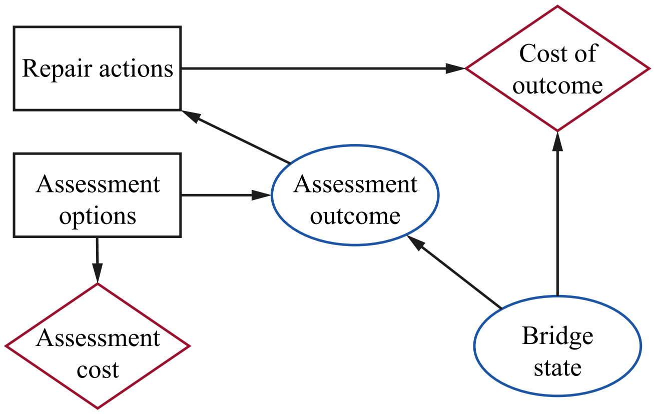


Fig. 2. An influence diagram for decision support under uncertainty. Reproduced after [4].

formulated based on the expected utility conditionally on the assessment outcome. If assessment option e_n has been selected showing the outcome z_k, the expected utility of repair action r_j can be computed as

$$E[u(e_n, z_k, r_j)] = P[z_k] \sum_i (u(r_j, e_n, z_k, \theta_i) P[\theta_i | z_k]) \tag{12}$$

where $E[u(\cdot)]$ is the expected utility, $u(\cdot)$ is the utility, $P[z_k]$ is the probability of z_k, and $P[\theta_i|z_k]$ is the updated probability of θ_i considering the outcome z_k. The decision on what repair action to implement is based on the maximum utility determined as

$$E[u(e_n, z_k)] = P[z_k] \max_j \left[\sum_i (u(r_j, e_n, z_k, \theta_i) P[\theta_i | z_k]) \right] \tag{13}$$

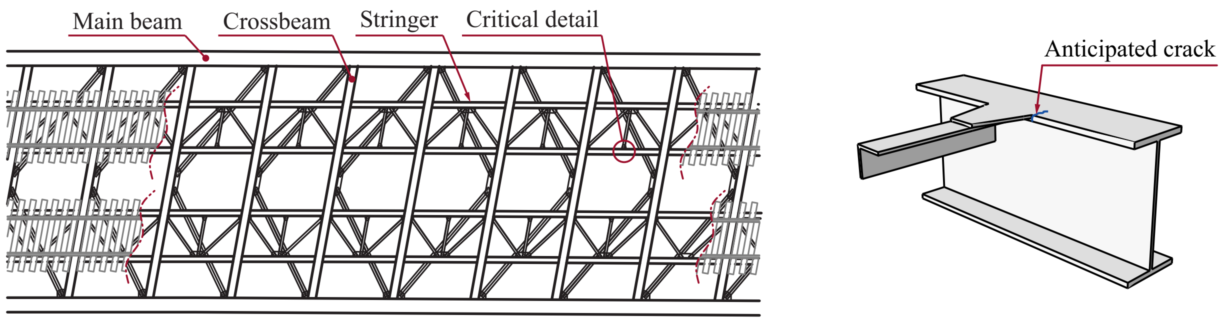
The expected utility for any assessment option is computed by evaluating Eq. (13) for all possible outcomes $(z_1, ..., z_K)$

$$E[u(e_n)] = \sum_k \left(P[z_k] \max_j \left[\sum_i (u(r_j, e_n, z_k, \theta_i) P[\theta_i | z_k]) \right] \right) \tag{14}$$

The assessment option rendering the maximum expected utility estimated using Eq. (14) should be selected. The evaluation scheme is the same as for a Bayesian preposterior analysis using a traditional decision tree which has been treated extensively in, e.g., [24]. The graphical representation of an influence diagram is, however, preferred when the dimensions of the problem grow. The analysis of the decision problem can be performed using, e.g., the freely available software GeNIe Modeler [25]. The numerical example presented in the following section was analysed using a routine developed in Matlab [26].

4. Case study

To demonstrate the suggested framework, an assessment scenario for a steel railway bridge in Sweden is used. The Söderström Bridge located in the city center of Stockholm is a vital part of the main railway line, loaded by long distance trains and local commuter trains. Several investigations have indicated an exhausted fatigue life but due to its critical position in the transport infrastructure, it must remain in service until a new traffic solution is in place. This means that extraordinary assessment actions are



(a) A plan view of a section of the Söderström Bridge. (b) The critical detail.

Fig. 3. The welded connection between the lateral bracing and the stringer beam on the Söderström Bridge.

motivated to ensure the structural safety. Preliminary assessments have shown that the connection of the lateral bracing to the stringer beams is one of the most critical details [22]. The detail is shown in Fig. 3. The same case has been used in [27] and in the European COST Action TU1402 (http://www.cost-_tu1402.eu/) but in different scenarios.

4.1. Assessment scenario

Due to the result of the preliminary assessment, a monitoring campaign was performed during the autumn 2008 to determine the stress variation caused by the actual traffic. Inspections have also been performed regularly over the years. A decision scenario is elaborated on the following assessment levels

(i) Preliminary deterministic assessment
(ii) e_0– Prior reliability-based assessment using measured stresses
(iii) e_1– Assessment based on LEFM without inspection
(iv) e_2– Assessment based on LEFM with visual inspection
(v) e_3– Assessment based on LEFM with magnetic particle testing

In relation to the MUK approach, the preliminary assessment (i) corresponds to the origin. Level (ii) entails steps in all three directions, M, U, and K, involving a new prediction model, a reliability-based format, and information from measurements. Level (iii) is a further step in the M direction when the prediction model is changed from linear damage accumulation to LEFM. Level (iv) and (v) are both steps in the K direction using information from inspections.

The preliminary deterministic assessment should comply with the governing regulations using information from drawings and standardized load models. Fatigue assessments are typically based on the safe life method considering fatigue endurances from tests and linear damage accumulation. This step can be performed as a pure desktop assessment and is not treated further in this example.

A prior estimation of the reliability is required for the decision framework. It has been computed using the limit state Eq. (6) based on the Palmgren-Miner rule, a stress range spectrum determined based on measurements, and the basic random variables listed in Table 1. The characteristic fatigue strength is classified to $\Delta\sigma_C = 40$ MPa based on the Eurocode [10]. This was used to calculate the mean value of $\ln K_1$ as described in [21]. The random variables are in principle assigned properties as suggested in [17]. The stress range spectrum and the prior reliability (level ii) are shown in Fig. 4.

As shown in Fig. 4, a target reliability of $\beta = 3.1$ is reached after about 8.6 million cycles which corresponds to about 3 years of service. If a replacement of the bridge is planned for 10 years ahead, the estimated reliability will have decreased to $\beta = 1.4$ as indicated in the figure. This is below the accepted target reliability and corresponds to a probability of failure of about 8.2×10^{-2}.

4.2. Decision support

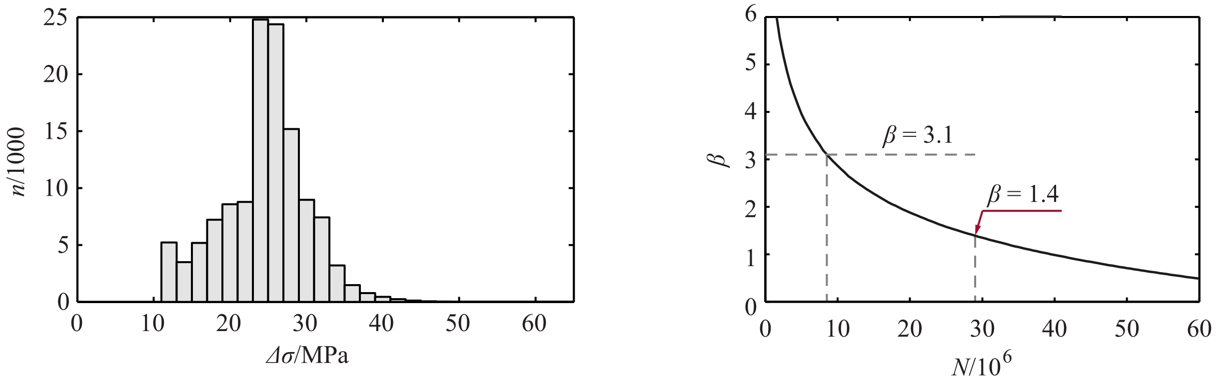
The influence diagram in Fig. 2 enables an evaluation of the different assessment actions (e_1 to e_3) before they actually have been performed. However, this requires sample likelihoods and utility functions. Tentative sample likelihoods were used as listed in Table 2 for the assessment actions. They reflect the expected accuracy of the actions as probabilities conditional on the true state of the bridge $P[z_k|\theta_i]$. As an example, the value $P[z_0|e_1, \theta_0] = 0.6$ means that for a true state of no failure, the assessment method will indicate no damage with a likelihood of 60 %, typically called a true negative.

Tentative values for the utilities were assigned as listed in Table 3 for the assessment actions and the random outcomes. The values should be seen as ratios between costs and not monetary values. A discussion about consequences and utility functions can be found in, e.g., [4] and [20].

Assigning a prior probability of failure $P_f = 8.2 \times 10^{-2}$ and using the values listed in Tables 2 and 3 give the expected utilities shown in Fig. 5 (a). The result shows that the expected utility increases with assessment level from a value of − 82 for the prior

Table 1
Basic random variables. N ~ Normal, LN ~ Lognormal, DET ~ Deterministic. The values are valid for crack growth in mm/cycle and stress intensity in MPa$\sqrt{\text{mm}}$.

Linear damage accumulation				LEFM			
Variable	Distrib.	Mean	CoV	Variable	Distrib.	Mean	CoV
δ	LN	1	0.3	C_S	LN	1	0.04
C_S	LN	1	0.04	C_{SIF}	LN	1	0.07
$\ln K_1$	N	26.1	0.49	A_a	LN	$4.80 \cdot 10^{-18}$	1.70
K_2	Fully correlated to K_1			A_b	LN	$5.86 \cdot 10^{-13}$	0.60
m_1	DET	3	–	m_a	DET	5.10	–
m_2	DET	5	–	m_b	DET	2.88	–
$\Delta\sigma$	DET	–	–	K_{th}	LN	140	0.40
				a_0	LN	0.15	0.66
				a_c	DET	113	–
				$\Delta\sigma$	DET	–	–



(a) Stress range spectrum based on measurements. (b) Prior reliability.

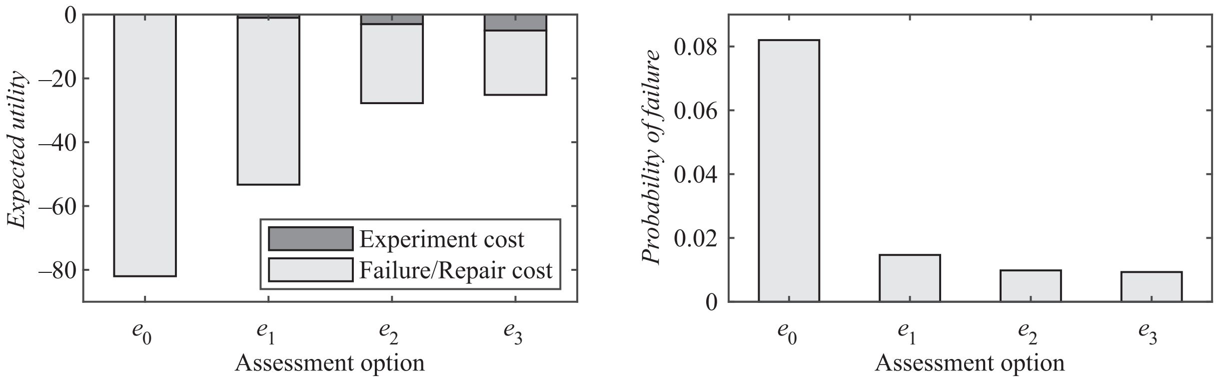
Fig. 4. Stress range spectrum and prior reliability for the case study.

Table 2
Tentative sample likelihoods for the case study, $P[z_k|\theta_i]$. Bridge state θ_0 ~ no failure, θ_1 ~ failure.

	Assessment e_1		Assessment e_2		Assessment e_3	
	Detail state		Detail state		Detail state	
Assessment result	θ_0	θ_1	θ_0	θ_1	θ_0	θ_1
Indicates no damage	0.6	0.1	0.9	0.1	0.95	0.1
Indicates damage	0.4	0.9	0.1	0.9	0.05	0.9

Table 3
Utilities for the assessment actions and the random outcomes.

Assessment costs				Cost of outcome			
				No failure, θ_0		Failure, θ_1	
e_0	e_1	e_2	e_3	No repair	Repair	No repair	Repair
0	−1	−3	−5	0	−100	−1 000	−100



(a) Expected utility. (b) Posterior probability of failure.

Fig. 5. Results from the evaluation of the assessment scenario for the case study.

assessment to − 25 for the assessment option e_3. This supports a decision to procure an assessment based on LEFM combined with inspections using magnetic particle testing. It is, however, important to also look at the possible increase in reliability level. The posterior probabilities of failure are shown in Fig. 5 (b). The assessment actions may decrease the probability of failure to a minimum of $P[\theta_0|z_0] = 9.3 \times 10^{-3}$ which corresponds to a reliability index of about $\beta = 2.35$, on the condition that no damage is found.

The expected utility of the assessment scenario is strongly dependent on the ratio between the costs of repair and failure. A study

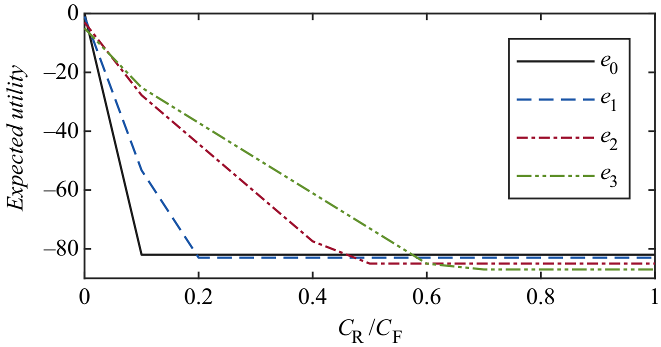


Fig. 6. The expected utility as a function of the ratio between the costs of repair (C_R) and failure (C_F). The cost of failure was kept at a constant value of $C_F = -1000$.

on the influence of the repair cost is shown in Fig. 6, where the x axis shows the ratio between the repair cost (C_R) and the failure cost (C_F). For low cost of repair, the outcome will favour no further actions. Repairing the structure will be more beneficial than paying for an uncertain assessment. For a high repair cost, the cost of failure will always be decisive which renders the plateau in the figure. Between the two extremes, the cost of failure will be decisive if no damage is indicated, and the cost of repair if damage is found. For the studied bridge, a low ratio C_R/C_F is expected due to high consequences of a failure while a planned repair action is assumed to be less costly. The result in Fig. 6 is in line with the numerical example in [4].

The results in Fig. 6 indicate the importance of the sample likelihoods from Table 2. The location C_R/C_F where the plateau starts differ significantly between the assessment options e_0 to e_3. This highlights the importance of assigning adequate values for the sample likelihoods which is an area for future research.

4.3. Validation

The decision analysis should be performed before the possible assessment actions have been engaged and shows the expected outcome. Fig. 7 shows the results when the actions have been performed on the condition that no damage is found during the inspections. The limit state Eq. (8) for LEFM was used to estimate the reliability together with the basic random variables listed in the right part of Table 1. The reliability updating was performed assuming an inspection at 20 million cycles with no detected crack. The lower level detectability, a_d in Eq. (11), for visual inspection (VT) and magnetic particle testing (MT) was considered as suggested in [28].

As shown in Fig. 7, the reliability will improve more than the decision model predicted, on the condition that no damage is found during inspections. These results reflect a posterior analysis given evidence of an outcome for each assessment action; i.e. the outcome of these actions is no longer random. For the setup of the case study, the proposed decision support framework is able to give an adequate proposal. Assessment action e_3, a method based on LEFM in combination with magnetic particle testing, provides the largest expected utility and renders the highest updated reliability.

5. Conclusions

A decision support framework has been presented and the application to fatigue assessment of steel bridges has been described. The framework is aimed to facilitate the procurement of enhanced assessments of existing structures. The practical implementation has been demonstrated using a case study bridge.

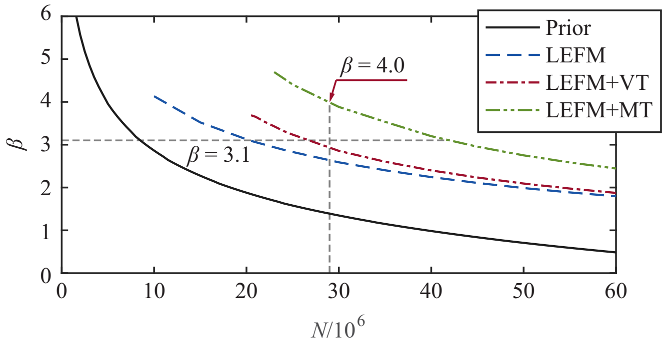


Fig. 7. The estimated reliabilities considering the different assessment actions and no detected crack at an inspection at 20 million cycles.

The MUK approach visualized in Fig. 1 allows a distinction between different assessment actions. It builds on three attributes, model sophistication (M), uncertainty consideration (U), and knowledge content (K). Through the MUK approach, a decision maker can consider a number of possible approaches for evaluating the condition of a bridge. The model has been used to classify established methods for fatigue assessment and it has been shown how different alternatives can be combined to yield to an increased confidence in the result. For example, the authors investigated how information from inspections can be combined with a theoretical prediction model. To navigate the MUK triplet, a risk-based evaluation using an influence diagram is suggested, allowing a rational evaluation of different assessment options.

The case study shows that the ratio between the failure and repair cost has a significant influence on the expected utility, and thereby which alternative to prefer. A validation of the result shows that the proposed decision support framework is able to give an adequate proposal. Assessment action e_3, a method based on LEFM in combination with magnetic particle testing, provides the largest expected utility and renders the highest updated reliability in this case.

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References

[1] Sustainable Bridges, Guideline for Load and Resistance Assessment of Existing European Railway Bridges, Sustainable Bridges - Assessment for future traffic demands and longer lives, 2007 http://www.sustainablebridges.net.
[2] ASCE, ASCE's 2017 Infrastructure Report Card, (2017) http://www.infrastructurereportcard.org.
[3] B. Kühn, M. Lukic, A. Nussbaumer, H. Günther, R. Helmerich, S. Herion, M. Kolstein, S. Walbridge, B. Androic, O. Dijkstra, O. Bucak, Assessment of existing steel structures: recommendations for estimation of remaining fatigue life, Prepared under the JRC-ECCS cooperation agreement for the evolution of Eurocode, 3 2008.
[4] I. Björnsson, O. Larsson Ivanov, D. Honfi, J. Leander, Decision Support Framework for Bridge Condition Assessments, (2018) Submitted for Review.
[5] ISO 13822, Bases for design of structures - assessment of existing structures, (2010).
[6] U.B. Kjærulff, A.L. Madsen, Bayesian Networks and Influence Diagrams - A Guide to Construction and Analysis, Springer, New York, 2008.
[7] E. Arzaghi, M.M. Abaei, R. Abbassi, V. Garaniya, C. Chin, F. Khan, Risk-based maintenance planning of subsea pipelines through fatigue crack growth monitoring, Eng. Fail. Anal. 79 (2017) 928–939.
[8] J.J. Nielsen, J.D. Sørensen, Bayesian NetwAorks as a decision tool for O&M of offshore wind turbines, ASRANet: Integrating Structural Analysis, Risk & Reliability: 5th International ASRANet Conference, ASRANet Ltd., 2010.
[9] J.D. Sørensen, Framework for risk-based planning of operation and maintenance for offshore wind turbines, Wind Energy 12 (5) (2009) 493–506.
[10] CEN, EN 1993-1-9. Eurocode 3: design of steel structures-Part 1.9: Fatigue, (2006).
[11] A.F. Hobbacher, Recommendations for Fatigue Design of Welded Joints and Components, International Institute of Welding, 2007 IIW document XIII-2151-07/XV-1254-07.
[12] M. Aygül, M. Bokesjö, M. Heshmati, M. Al-Emrani, A comparative study of different fatigue failure assessments of welded bridge details, Int. J. Fatigue 49 (2013) 62–72.
[13] A. Fatemi, L. Yang, Cumulative fatigue damage and life prediction theories: a survey of the state of the art for homogeneous materials, Int. J. Fatigue 20 (1) (1998) 9–34.
[14] P.C. Paris, M.P. Gomez, W.E. Anderson, A rational analytic theory of fatigue, Trend Eng. 13 (1) (1961).
[15] BSI, BS 7910 Guide to Methods for Assessing the Acceptability of Flaws in Metallic Structures, The British Standards Institution (BSI), 2013.
[16] A.F. Hobbacher, Stress intensity factors of plates under tensile load with welded-on flat side gussets, Eng. Fract. Mech. 41 (6) (1992).
[17] JCSS, Probabilistic Model Code - Part 3: Resistance Models, Joint Committee on Structural Safety (JCSS), (2011).
[18] J. Leander, M. Al-Emrani, Reliability-based fatigue assessment of steel bridges using LEFM - a sensitivity analysis, Int. J. Fatigue 93 (2016) 82–91.
[19] J.J. Nielsen, J.D. Sørensen, On risk-based operation and maintenance of offshore wind turbine components, Reliab. Eng. Syst. Saf. 96 (1) (2011) 218–229.
[20] J. Goyet, V. Boutillier, A. Rouhan, Risk based inspection for offshore structures, Ships Offshore Struct. 8 (3-4) (2013) 303–318.
[21] J. Leander, B. Norlin, R. Karoumi, Reliability-based calibration of fatigue safety factors for existing steel bridges, J. Bridg. Eng. 20 (10) (2015) 1–9.
[22] J. Leander, A. Andersson, R. Karoumi, Monitoring and enhanced fatigue evaluation of a steel railway bridge, Eng. Struct. 32 (3) (2010).
[23] H.O. Madsen, S. Krenk, N.C. Lind, Methods of Structural Safety, Dover Publications Inc., New York, 2006.
[24] J.R. Benjamin, C.A. Cornell, Probability, Statistics, and Decisions for Civil Engineers, McGraw-Hill Book Company, New York, 1970.
[5] BayesFusion, LLC, GeNIe Modeler, (2017) http://www.bayesfusion.com.
[26] The MathWorks, Inc., matlab, Natick, Massachusetts, United States, (2017) version R2017b.
[27] J. Leander, D. Honfi, Ívar Björnsson, Risk-based planning of assessment actions for fatigue life prediction, Proc. Struct. Integr. 5 (2017) 1221–1228.
[28] J. Leander, E. Selén, The applicability of reliability-based inspection planning for steel bridges based on fatigue crack detection, in: C. Bucher, B.R. Ellingwood, D.M. Frangopol (Eds.), Proceedings of 12th Int. Conf. on Structural Safety and Reliability (ICOSSAR), 2017, pp. 2396–2405.