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Utility analysis for SHM durations and service life extension of welds on steel bridge deck

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ABSTRACT

Optimization of the duration of Structural Health Monitoring (SHM) campaigns is rarely performed. This article provides a utility-based solution to posteriorly determine: i) optimal monitoring durations and ii) the extension of the service life of the welds on a steel bridge deck. The approach is illustrated with a case study focusing on remaining fatigue life estimation of the welds on the orthotropic steel deck of the Great Belt Bridge, in Denmark. The identification of the optimal monitoring duration and the decision about extending the service life of the welds are modelled by maximizing the expected benefits and minimizing the structural risks. The results are a parametric analysis, mainly on the effect of the target probability, benefit, cost of failure, cost of rehabilitation, cost of monitoring and discount rate on the posterior utilities of monitoring strategies and the choice of service life considering the risk variability and the costs and benefits models. The results show that the decision on short-term monitoring, i.e., 1 week every six months, is overall the most valued SHM strategy. In addition, it is found that the target probability is the most sensitive parameter affecting the optimal SHM durations and service life extension of the welds.

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Fatigue; monitoring strategy; orthotropic steel deck; structural health monitoring; utility and decision theory

1. Introduction

Many studies on Structural Health Monitoring (SHM) have been made available in recent decades (e.g., Balageas, Fritzen, & Güemes, 2010; Farrar & Worden, 2007; Sohn et al., 2003). These studies focus mainly on data acquisition, normalization, cleaning, feature extraction and information condensation (Farrar et al., 2003; Farrar & Worden, 2012; Sohn et al., 2003). In the past decade, one of the main research topics in SHM was using monitoring for the management of structures (Okasha & Frangopol, 2012; Orcesi & Frangopol, 2011; Pozzi, Zonta, Wang, & Chen, 2010). Among these works, Vanik et al. presented a Bayesian probabilistic approach to SHM (Vanik, Beck, & Au, 2000). Wenzel et al. related the life cycle management for civil structures to SHM (Wenzel, Veit-Egerer, Widmann, & To, 2011). Flynn and Todd (2010) developed an approach for optimising sensor placement of a SHM system.

Herein, the optimal SHM system is the one leading to the lowest Bayes risk (expected loss) in the context of the operational modelling of the SHM (Flynn & Todd, 2010; Todd, Haynes, & Flynn, 2011). In continuation of research progress, it has been gradually acknowledged that without a decision analytical framework including the structural system performance, the SHM information cannot be optimally utilized for the structural integrity management. Pozzi & Der Kiureghian, Faber & Thöns, and Straub proposed and worked on utilizing

Value of Information (VoI) theory to quantify the SHM performance (Faber & Thöns, 2013; Pozzi, Der Kiureghian, & Kundu, 2011; Straub, 2014). Based on this approach, the ideal SHM strategy is the one found with highest VoI (expected utility gain) identified with a decision analysis.

The quantified value of SHM information has been utilized to assess the impact of the SHM on decision-making (Zonta, Glisic, & Adriaenssens, 2014) to optimise the structural integrity management (Qin, Thöns, & Faber, 2015) to evaluate a road viaduct fatigue safety (Bayane, Long, Thöns, & Brühwiler, 2019) and to optimize the sensor configuration for damage detection systems (Long, Döhler, & Thöns, 2020; Long, Thöns, & Döhler, 2018). Moreover, in the framework of European project of COST Action TU1402 (Diamantidis, Sykora, & Sousa, 2019; Sousa, Wenzel, & Thöns, 2019; Thöns, 2019): “Quantifying the Value of Structural Health Monitoring” (<https://www.cost-tu1402.eu/>) detailed guidelines have been developed for operators, engineers and scientists on quantifying the value of Structural Health Information (SHI) for Decision Support.

However, in the field of SHM supported structural integrity management, there are still open questions. One of the issues is permanent versus short-term/periodic monitoring (del Grosso, 2013). Permanent monitoring is relatively expensive and may produce a very large amount of data

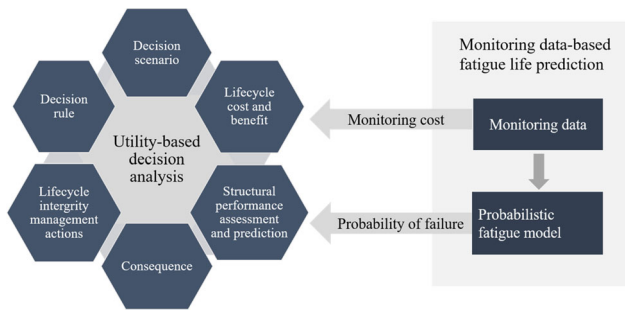


Figure 1. Road map of the proposed methodology.

requiring complex data transmission and management resources. Periodic monitoring is performed with temporary SHM installations on structures collecting data for a short time in defined intervals facilitating instrumentation use for multiple structures. Moreover, portable units may be deployed to maximize the spatial coverage of structures.

The focus of the article aims thus to provide new insights to strengthen the understanding of permanent versus periodic monitoring in the case of long-term deterioration assessment (fatigue) and to explore novel methodologies to rationalize the use of monitoring (permanent versus periodic) through utility-based decision analysis. For this, a methodology is illustrated with strain and temperature data used to assess a long-term deterioration mechanism as fatigue. Although the monitoring system was permanently installed, one could think of scenarios where sensors have been installed but not the acquisition units via Unmanned Aerial Vehicles. This would allow for monitoring a number of structures by having a limited number of data acquisition units (expensive equipment). For other mechanisms (e.g., to assess movement of bearings or articulations), one could reason similarly: use short-term monitoring strategies and then move the equipment to other structures.

This article posteriorly compares the SHM strategies in regard to monitoring durations based on a reference continuous monitoring dataset through utility-based decision analysis. The utility-based decision analysis is the basis of VoI analysis, in which the VoI is defined as the expected utility gain between (pre)-posterior decision analysis and prior decision analysis (Raiffa & Schlaifer, 1961). In this paper, a utility-based posterior decision analysis is implemented based on the obtained monitoring information to optimize SHM strategies posteriorly in terms of monitoring durations, in the case that the prior information of the structure is not available. With this study, it is envisaged to provide:

1. a methodology to extend the fatigue service life of the welds based on periodic monitoring,
2. a quantification on the duration of those periodic monitoring, and
3. a comprehensive understanding of the main parameters influencing the optimal decisions on the monitoring strategies.

The article starts by introducing the methodology employed for selecting optimal monitoring strategies and deciding to extend the service lives of welded joints. This

includes utility theory and posterior decision analysis as well as specific data-driven probabilistic models employed to estimate remaining fatigue lives building upon the previous article by the authors (Long, Alcover, & Thöns, 2019). The proposed theoretical approach is then illustrated with a case study from the Great Belt Bridge. The monitoring data has been split between four options to simulate the case of periodic monitoring for the purpose of the article. The posterior expected utilities of different monitoring strategies are quantified and the optimal monitoring strategy and decision on service life extension of the instrumented welds are determined.

2. Methodology

The methodology section introduces the principles of both utility-based decision analysis and monitoring data-based fatigue life predictions, which is shown in Figure 1. The utility-based decision analysis solves the lifecycle integrity management problems considering structural performance assessment and prediction, consequences and lifecycle cost and benefit, with establishment of the decision scenarios and decision rules. The monitoring data-based fatigue life prediction provides input information for the utility-based decision analysis, such as monitoring costs and probability of fatigue failure based on a probabilistic fatigue model.

2.1. Utility-based decision analysis

The utility theory dates back to 1738 when Bernoulli defined that the value of an object must not be determined on the basis of the price or cost, but instead on the utility it yields (Bernoulli, 1738). Inspired by Bernoulli's hypothesis, Von Neumann et al. used it as a foundation to build their game theory in 1944, which is applicable to various contexts (Von Neumann, Morgenstern, & Kuhn, 2007). Furthermore, in 1961 Raiffa and Schlaifer formulated the decision theory (Raiffa & Schlaifer, 1961). This is now applied to the field of SHM and used for quantifying the value of monitoring information.

The decision process can be illustrated in a decision tree, as shown in Figure 2. According to Raiffa and Schlaifer, a utility (monetary) function $u(e, z, a, \theta)$ is assigned to a decision maker to describe the decision consequences when performing an experiment e , e.g., a SHM strategy according to (Faber & Thöns, 2013; Pozzi & Der Kiureghian, 2011); observing a particular outcome z , e.g., detecting damage or not; taking a particular action a , e.g., repair, replace or do-nothing; and then obtaining a particular state of a structure θ , e.g., safe, damaged or failed. The utility function should contain the total cost and benefits throughout the decision process. The total cost will be the sum of the costs of consequences (failure costs considering fatalities, economic, environmental and social impacts); the cost of actions (e.g., repair cost); and the cost of monitoring (strain gauges investment, installation, operation and replacement costs, etc.). The benefits are related to the socio-economic effects for the state and company e.g., from toll charges and for the users, e.g., time saving and for the environment, e.g., from reduction of CO₂ emissions.

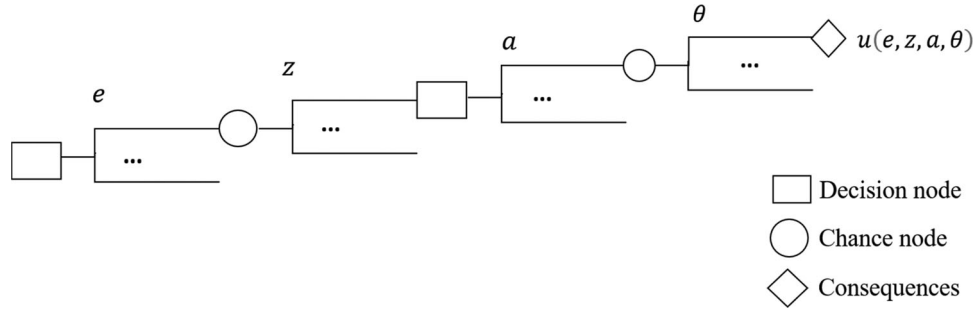


Figure 2. Illustration of a decision tree.

However, the state of the structure is subjected to uncertainties. Therefore, a probability $P(e, z, a, \theta)$ needs to be assigned to represent the belief of knowledge of the decision maker regarding the state of the structure θ after implementing a strategy e , obtaining the outcome z and taking an action a . There may be m states in total for the structure, e.g., damaged, undamaged, slightly damaged or failed, etc. So that the expected utility $U(e, z, a, \theta)$ can be written as:

$$U(e, z, a, \theta) = \sum_{j=1}^m u(e, z, a, \theta_j) \cdot P(e, z, a, \theta_j) \quad (1)$$

Depending on how much information is available at the time of decision making, the probabilities of the system states $P(e, z, a, \theta)$ can be differentiated as prior probability when only the design information of the structure is known, posterior probability when additional SHM information is obtained and pre-posterior probability when SHM information is modelled and predicted but not yet implemented. The expected utility $U(e, z, a, \theta)$ will be termed accordingly as prior utility, posterior utility and pre-posterior utility (Faber, 2012).

When considering SHM, inspection and repair planning within the lifecycle integrity management, the expected utility during service life U_{SL} can be formulated as:

$$U_{SL} = U_B - U_F - U_R - U_I - U_M \quad (2)$$

where:

$$U_B = \sum_{t=1}^{T_{SL}} B(t) \cdot (1 - P(F_t)) \cdot \frac{1}{(1 + \gamma)^t}$$

$$U_F = \sum_{t=1}^{T_{SL}} C_F(t) \cdot \Delta P(F_t) \cdot \frac{1}{(1 + \gamma)^t}$$

$$U_R = \sum_{i=1}^{N_R} C_R(T_i) \cdot P(R_{T_i}) \cdot (1 - P(F_{T_i})) \cdot \frac{1}{(1 + \gamma)^{T_i}}$$

$$U_I = \sum_{j=1}^{N_I} C_I(T_j) \cdot (1 - P(F_{T_j})) \cdot \frac{1}{(1 + \gamma)^{T_j}}$$

$$U_M = \sum_{m=1}^{N_M} C_M(T_m) \cdot (1 - P(F_{T_m})) \cdot \frac{1}{(1 + \gamma)^{T_m}}$$

where, U_B is the expected total lifecycle benefits, U_F is the expected total cost of failure during service life, U_R is the expected total lifecycle repair costs, U_I is the expected total inspection costs during service life, U_M is the expected total monitoring costs. In addition, $B(t)$ is the annual benefit at

year t , $C_F(t)$ is the cost of failure at year t , $C_R(T_i)$ is the cost of repair at repair year T_i , $C_I(T_j)$ is the cost of inspection at inspection year T_j , $C_M(T_m)$ is the cost of monitoring at monitoring year T_m , N_R is the total number of repair, N_I is the total number of inspection, N_M is the total number of monitoring; $P(F_t)$ is the probability of failure at year t ; $\Delta P(F_t)$ is the annual probability of failure at year t . $P(R_{T_i})$ is the probability of repair at repair year T_i ; T_{SL} is the service life; γ is the discounting rate. It is noted that a decision rule will normally be introduced to simplify the decision process, e.g. an action is required if the reliability reaches a specified target probability P_{Target} .

The integrity management of a structure usually involves multiple choices of actions and SHM strategies. The optimal choice of action and SHM strategies is found through maximizing the expected utilities of different actions and SHM strategies during service life. The optimal action and strategy will result in the highest expected utility. In order to systematically analyse the expected utility influencing parameters beyond the probabilistic engineering models, the target probability P_{Target} , benefit B , failure cost C_F , inspection costs C_I , repair cost C_R , monitoring cost C_M and discount rate γ will be parametrically analysed in the frame of a posterior decision analysis in Section 4. The posterior probability of failure will be calculated using probabilistic data-based models described in Section 2.2.

2.2. Monitoring data-based fatigue life prediction

The monitoring data-based probabilistic model is built on three types of data as show in Table 1: pavement temperatures acquired from temperature sensors, vehicle traffic counts obtained from a toll system and strain data obtained from strain gauges. The following is a brief summary of the monitoring data-based probabilistic model as shown in Figure 3, for a detailed and comprehensive model description it can be referred to (Farreras-Alcover, Chryssanthopoulos, & Andersen, 2017).

Fluctuations of the average of the pavement temperatures \bar{T}_t are modelled by a generic sinusoidal function with parameters α_1 , α_2 , α_3 and m_T :

$$\bar{T}_t = \alpha_1 \cdot \sin(\alpha_2 \cdot t + \alpha_3) + m_T \quad (3)$$

Daily-averaged pavement temperatures $T_{\Delta t}$ is de-seasonalized by deducting the daily mean value \bar{T}_t and then differentiated by the monthly standard deviation $\sigma_{T,t}$ of the time series:

Table 1. Summary of the monitoring data from the monitoring system.

Monitoring system	Monitoring data
Temperature sensor	Pavement temperature
Toll system	Vehicle traffic counts
Strain gauges	Strain data

$$T_t^* = \frac{T_{\Delta t} - \bar{T}_t}{\sigma_{T,t}} \quad (4)$$

The de-seasonalized daily-averaged pavement temperature T_t^* is further fitted to an autoregressive (AR) model, where $\varphi_{T,1}$ is the coefficient of AR model and $\epsilon_{T,t}$ is a random normal error parameter at time t :

$$T_t^* = \varphi_{T,1} \cdot \bar{T}_{T,t-1} + \epsilon_{T,t} \quad (5)$$

Similarly, the heavy daily-aggregated traffic count $B_{\Delta t}$ is firstly de-seasonalized to $B_{\Delta t}^*$ by subtracting the daily average $\mu_{B,t}$ and divided by the weekly standard deviation $\sigma_{B,t}$ of the time series:

$$B_{\Delta t}^*(t) = \frac{B_{\Delta t} - \mu_{B,t}}{\sigma_{B,t}} \quad (6)$$

A regression model is applied to identify the day-of-the-week effect on the de-seasonalized time series $B_{\Delta t}^*$ with the parameters λ_i (i th regression coefficient), $X_{i,t}$ (i th dummy descriptive variable) and $\epsilon_{B,t}$ (random error process parameter at time t):

$$B_{\Delta t}^*(t) = \sum \lambda_i \cdot X_{i,t} + \epsilon_{B,t} \quad (7)$$

The traffic regression model's residuals are modelled by an AR model where $\epsilon_{B,t}$ is the regression error at time t , $\varphi_{B,i}$ is the parameter of the AR model, p is the order of the AR model and v_t is a normal random error parameter:

$$\epsilon_{B,t} = \sum_{i=1}^p \varphi_{B,i} \cdot \epsilon_{B,t-1} + v_t \quad (8)$$

The daily-aggregated fatigue loading at a given welded joint, $D_{\Delta t}$, is conservatively calculated from Equation (9), where $\Delta\sigma_i$ is the i th stress range out of the total amount of stress cycles N_C within the time step Δt (1 day) and m is the SN endurance curve slope:

$$D_{\Delta t}(t) = \sum_{i=1}^{N_C} \Delta\sigma_i^m \quad (9)$$

In orthotropic steel decks, the key causes of fatigue damage are pavement temperatures and heavy traffic intensities. Hence, a regression model among daily-averaged pavement temperatures $T_{\Delta t}$, daily-aggregated heavy traffic counts $B_{\Delta t}$ and daily-aggregated SN fatigue loading $D_{\Delta t}$ is introduced by (Alcover, 2014). The left term in Equation (10) can be regarded as normalized fatigue loading per heavy vehicle when considering SN curve with fatigue parameter $m = 3$, which is for simplification conservatively considered as single-sloped with no cut-off limit:

$$\frac{D_{\Delta t}}{B_{\Delta t}}(T_0) = \theta_w \cdot T_0 \pm t_{n-p-1} \cdot s_{tot} \quad (10)$$

where $T_0 = [1 \ T_0^1 \ \dots \ T_0^p]^T$ is a specified temperature of the pavement for which the forecast band is computed, θ

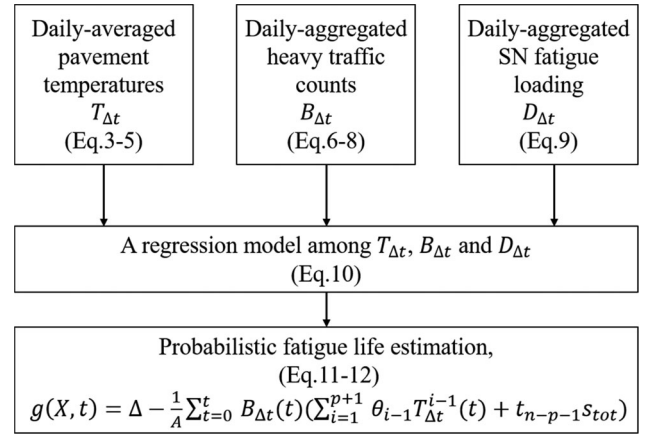


Figure 3. Flow chart of monitoring data-based probabilistic model.

are the parameters of the regression model, n the number of data points corresponding to the training dataset associated used to approximate the regression parameters, p the order of the regression model, t_{n-p-1} a t-distribution with $n - p - 1$ degrees of freedom and s_{tot} the estimate of the overall regression model variance at a given $T_{\Delta t}(t)$.

The fatigue limit state function can be described on the basis of the SN curves to measure fatigue damage and with Miner's accumulation law:

$$g(X, t) = \Delta - \frac{1}{A} \cdot \sum_{i=1}^t D_{\Delta t}(t) \quad (11)$$

where X is the random variables vector, Δ is Miner's sum at failure (Miner's Rule is one of the most used cumulative damage equations for failures caused by fatigue. When the sum of damage fractions is greater than 1.0, it will lead to failure), A is the material parameter defining the SN fatigue curve. Considering the above succession of regression and time-series models considering daily-averaged pavement temperatures and daily-aggregated heavy traffic, the limit state function of fatigue is:

$$g(X, t) = \Delta - \frac{1}{A} \sum_{t=0}^t B_{\Delta t}(t) \left(\sum_{i=1}^{p+1} \theta_{i-1} T_{\Delta t}^{i-1}(t) + t_{n-p-1} s_{tot} \right) \quad (12)$$

The sensor measurement error could be further included in the probabilistic model define in Equation (12). However, the measurement error has been found to be insignificant due to the quality of the installed equipment and its calibration in comparison to the other uncertainties (e.g., fatigue damage parameter A , Miner's sum at failure, etc.).

The weld will fail when the accumulated fatigue damage is larger than Miner's sum at failure. So that the probability of failure $P(F_t)$ can be estimated via Monte Carlo Simulation method as follows:

$$P(F_t) = P(g(X, t) \leq 0) \quad (13)$$

The uncertainties of the monitoring-based model are considered through modeling the SN fatigue parameter and Miner's sum at failure as random variables not linked with SHM data. The uncertainties of the SHM data are treated on the process of deriving three different models for fatigue

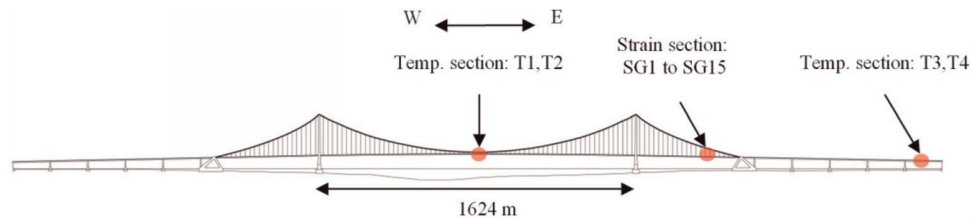


Figure 4. Illustration of Great Belt Bridge. (Temp. = Temperature, SG = Strain Gauge).

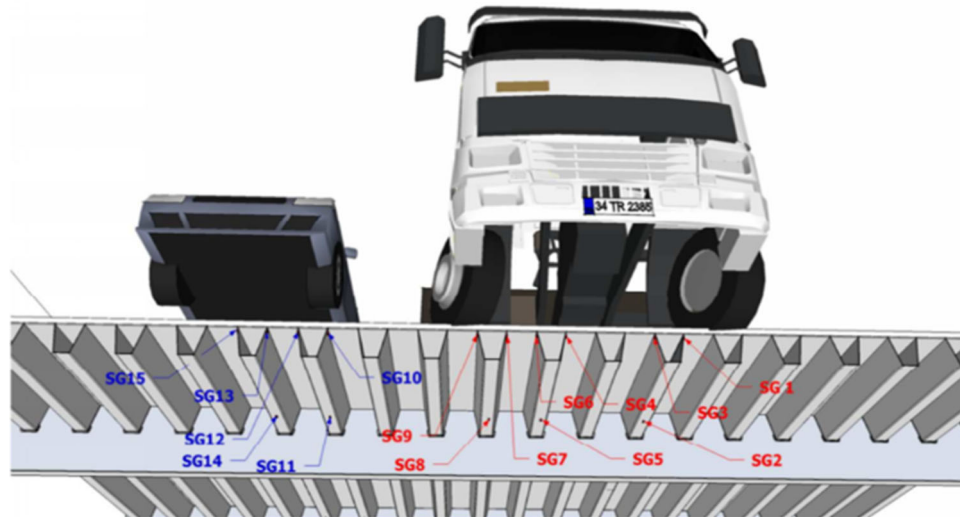


Figure 5. Illustration of strain monitoring system.

damage simulation: i) regression models for SN fatigue damage prediction (here the uncertainties are captured by the prediction bands of the models presenting described by $t_{n-p-1}S_{tot}$ in Equation (10)), ii) time-series models for temperature prediction and iii) time-series models for traffic prediction. The uncertainties of the time-series models are captured by the random error process associated to each model and characterized via SHM data.

The pavement temperatures impact stress ranges on orthotropic steel decks and thereby influence fatigue life due to pavement-steel composite action. The model presented in Equation (10) predicts the fatigue damage at a given detail per unit of heavy vehicle and at a given pavement temperature. Then, Equation (12) uses independent models for predicting heavy traffic counts and pavement temperatures. These models are eventually used to calculate fatigue damages. The results presented in the article correspond to a case with no increase of average pavement temperatures nor traffic levels than the ones used to derive the data-based models. The probabilistic model for data-based fatigue life prediction used in Equation (12) can consider different scenarios in terms of future average temperatures and traffic levels. This makes it possible to simulate unexpected events such as COVID-19 as they will have an impact on the daily number of heavy traffic vehicles used in the probabilistic model for fatigue prediction. In effect, vehicle counts and vehicle categories are monitored at the toll system of the bridge on an hourly basis; they have been used to

characterize the traffic model $B_{\Delta t}$ in Equation (12). More details can be found in (Farreras-Alcover et al., 2017).

3. Case study

The above approach is illustrated with a case study from the Great Belt Bridge, which is a suspension bridge with main span of 1624 m and maximum hanger length of 177 m in Denmark as shown in Figure 4. The cross-section of the orthotropic steel bridge deck (OSD) is formed with a closed steel box girder. Longitudinal troughs and crossbeams are located about 4 m apart on the OSD. The fatigue of through to deck weld and trough splice weld is considered with designed fatigue life of 100 years with certain fixed inspection intervals. Its operation started in 1998.

3.1. SHM system

In 2007, after approximately 10 years of operation, a comprehensive SHM system for design verification and condition monitoring was installed. The SHM system on the Great Belt bridge consists of, among others, a pavement temperature monitoring system, traffic monitoring system (used by the toll system) and strain monitoring system (Figure 5). The location of the fatigue prone details to be assessed was determined prior to the writing of the article to perform a fatigue assessment task on the two critical details for the orthotropic steel deck under consideration: a trough-to-deck weld (detail category 50

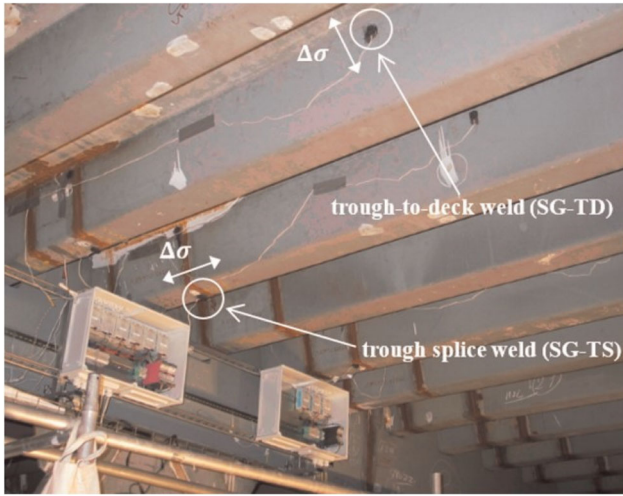


Figure 6. Strains gauges at welds (SG-TS = Strain Gauge Trough Splice, SG-TD: Strain Gauge Trough-to-deck).

according to EN1993-1-9-Part1-9) and a trough-splice weld (detail category 71 according to EN1993-1-9-Part1-9), as shown in Figure 6. Details on the fatigue prediction methodology can be found in (Farreras-Alcover, Andersen, & McFadyen, 2016).

A cross-sectional strain monitoring system instrumented consists of 15 uniaxial strain gauges (Figure 5), of which 10 gauges (i.e. 1,3,4,6,7,9,10,12,13,15) monitor the transverse nominal strains at the trough to deck weld, and 5 gauges (i.e. 2,5,8,11,14) monitor the longitudinal nominal strains at trough splice welds (Figure 6). Strain gauges 1 to 9 are positioned under the slow traffic lane, which is passed by the heavy vehicles, while the others are positioned under the fast traffic lane. Four temperature monitoring sensors are embedded into two different cross-sections of the pavement and record the temperature every 5 minutes. At the tollgate, the crossing vehicles are immediately recorded on an hourly basis according to their measurements.

3.2. SHM strategies

Farreras-Alcover et al. concluded that the measurement from SG8 (measured the trough splice weld) were associated with the highest fatigue loading (Farreras-Alcover et al., 2016). This weld is under the slow traffic lane where heavy vehicles run inducing higher stress cycles than at the fast lane. For convenience of demonstration, the modelling of SHM strategies is based on the training data sets from SG8 between February 2012 to July 2012, which is assumed to capture the entire temperature spectrum within a normal year owing to the regular repeatability of the temperature spread on the pavement (Farreras-Alcover et al., 2016).

According to the different monitoring phases and the time duration, four different monitoring strategies in terms of time durations are discussed as presented in Table 2. The reference monitoring option e_0 represents continuous monitoring for 168 days, option e_1 to option e_4 represent periodical monitoring with two phases of separate monitoring and 7, 14, 28, 42 monitoring days per phase respectively. The time windows associated with 4 options are selected based

Table 2. SHM strategies.

SHM strategies							Total days	Data used: %
e_1	■			■			14	8.3
e_2	■	■		■	■		28	16.6
e_3	■	■	■	■	■		56	33.3
e_4	■	■	■	■	■	■	84	50
e_0	■	■	■	■	■	■	168	100
	February	March	April	May	June	July		

on i) data availability and ii) consideration of representative 'extreme' weather conditions, i.e. data from February to July. In general, temperature variations are lower during cold conditions; hence this effect is accounted for in the calculated reliability profiles.

3.3. Fatigue life prediction

The fatigue life prediction is calculated following the probabilistic fatigue model from Section 2.2 and the variables in the probabilistic model are simulated following the model described in Table 3. The posterior probability of failure based on monitoring data $P(F_{t,e_i})$ for monitoring strategy e_i is calculated with Equation (13) and is shown in Figure 7(a), which increases with time. For the purposes of this study, it is assumed that when reliability profiles reach a certain target probability, it is required to take a certain action. The target probability is set as 10^{-4} (reliability index $\beta = 3.7$) according to the Joint Committee on Structural Safety (JCSS, 2001) considering normal relative costs of safety measures and minor consequences of failure. The weld is assumed to get rehabilitation after reaching the target probability. The probability of repair at the repair year is equal to the target probability. After the rehabilitation, the welds are assumed to behave as new and the posterior failure probability is assumed to be the failure probability in the year zero. The total number of rehabilitations depends on how many times it will reach the target probability during the whole service life.

Let $P(F_{t,e_i}|R_{t_R})$ be the posterior probability of failure after the rehabilitation event R_{t_R} implemented at year t_R with SHM strategy e_i ; t_R is the year in which the resulting posterior probability of failure $P(F_{t,e_i})$ dependent on monitoring data from strategy e_i is equivalent to the target probability P_{Target} . The posterior probability of failure after rehabilitation $P(F_{t,e_i}|R_{t_R})$ is calculated by:

$$P(F_{t,e_i}|R_{t_R}) = \begin{cases} P(F_{t,e_i}), & t < t_R = \arg(P(F_{t_R,e_i}) = P_{Target}) \\ P(F_{(t-t_R),e_i}), & t \geq t_R = \arg(P(F_{t_R,e_i}) = P_{Target}) \end{cases} \quad (14)$$

The posterior probability of failure after rehabilitation $P(F_{t,e_i}|R_{t_R})$ given reference SHM data is shown in Figure 7(b). It is worth noting that the fatigue reliability profiles are rather conservative considering single-slopped SN curves with no cut-off limit. The probabilistic models for the SN resistance are given in Table 3 for the two details considered. A slope of

Table 3. Variables of the probabilistic model.

Parameter	Symbol	Function	Distribution/Expression		Reference
			Mean	Standard deviation	
Trough-to-deck weld fatigue parameter	A	Lognormal	7.30E11	4.23E11	(Eurocode, 2005), (Jcss, 2001)
Trough-splice weld fatigue parameter	A	Lognormal	2.09E12	1.21E12	(Eurocode, 2005), (Jcss, 2001)
Miner's damage at failure	Δ	Lognormal	1.0	0.3	(Wirsching, 1995)
Daily heavy traffic counts	$B_{\Delta t}(t)$			Equations (6) – (8)	
Daily averaged pavement temperatures	$T_{\Delta t}(t)$			Equations (3) – (5)	

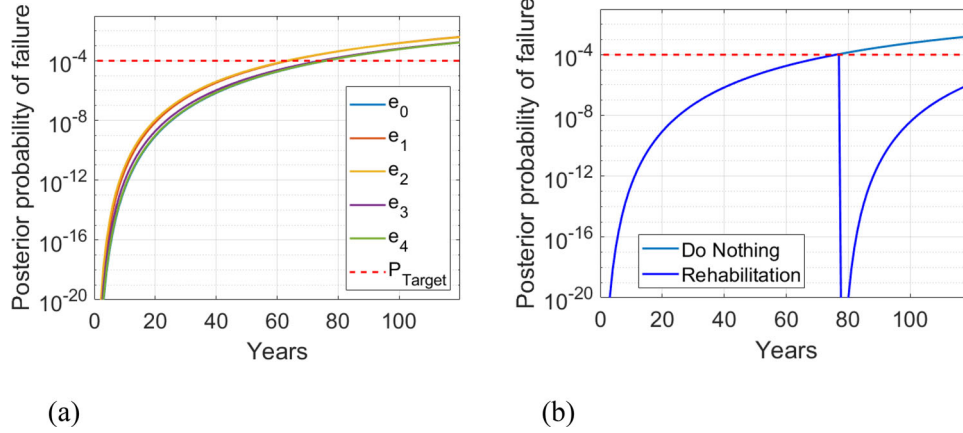


Figure 7. Prediction of probability of fatigue failure: (a) during service life of 120 years and with target probability (b) if doing nothing or rehabilitation given reference SHM data.

$m = 3$ is considered for the SN curve in log-scale (number of cycles to failure versus stress range). The above assumptions highlight that the results presented in the article shall be read as an illustration of the presented methodology for assessing optimal monitoring strategies, and not as representative of the actual fatigue life of the instrumented details.

3.4. Decision scenario

As mentioned before the welds are designed with a fatigue life of 100 years. After obtaining the predictions for fatigue life based on monitoring data, for the purpose of the investigation presented in this article, it aims to explore whether to extend the service life of the welds to 120 years. Given that different monitoring strategies provide different predictions of fatigue reliability profiles, it aims to figure out which monitoring strategy can achieve maximum utilities/benefits for the lifecycle integrity management to rationalize the use of SHM techniques for fatigue assessment.

A utility-based decision analysis is introduced in section 2.1 to solve the problem. The decision process is visualised in Figure 8 with a decision tree where a_i denoting the option of the actions, e.g., a_0 corresponding to a service life of 100 years and a_1 to an extended service life of 120 years. For different choices of the service life, the integrity of the welds needs to be managed, which involves planned rehabilitation costs C_R . The states of the welds θ_i are defined as safe state θ_1 and failure state θ_2 , which is effectively characterized by the fatigue reliability profiles. Welds will fail when the accumulated fatigue damage is larger than Miner's damage at failure. If the weld stays safe, the bridge will be operated normally with annual benefits B . If the weld fails, unscheduled rehabilitation events will be required, so that there will be a fatigue failure

cost C_F which will be the unscheduled rehabilitation cost. e_i represents the different monitoring strategies from Section 3.2. Given the different monitoring phases and monitoring durations, there will be different costs of monitoring C_M .

3.5. Utility calculation

U_{e_i} is to denote the expected maximum utilities regarding various actions with SHM strategy information e_i :

$$U_{e_i} = \max[U_{e_i, a_0}, U_{e_i, a_1}] \quad (15)$$

in which, U_{e_i, a_0} is the expected utility when the service life T_{SL} is kept at 100 years (a_0) with monitoring option e_i , U_{e_i, a_1} is the expected utility when the service life T_{SL} is extended to 120 years (a_1) with monitoring option e_i .

Let a_j represent a_0 and a_1 ($j = 0, 1$), then the expected utility U_{e_i, a_j} of the SHM strategy information e_i for taking action a_j is calculated by:

$$\begin{aligned}
 U_{e_i, a_j} = & \sum_{t=1}^{T_{SL, a_j}} (1 - P(F_{t, e_i} | R_{t_R})) \cdot B \cdot \frac{1}{(1 + \gamma)^t} \\
 & - \sum_{t=1}^{T_{SL, a_j}} \Delta P(F_{t, e_i} | R_{t_R}) \cdot C_F \cdot \frac{1}{(1 + \gamma)^t} \\
 & - \sum_{n=1}^{N_{m, e_i}} C_M \cdot (1 - P(F_{t_m, e_i} | R_{t_R})) \cdot \frac{1}{(1 + \gamma)^{t_m}} \\
 & - \sum_{n=1}^{N_{R, a_j}} C_R \cdot (1 - P(F_{t_R, e_i} | R_{t_R})) \cdot \frac{1}{(1 + \gamma)^{t_R}}
 \end{aligned} \quad (16)$$

It has to be noted that in Equation (16), there is either a_0 or a_1 , but not both in the same time; B is the annual

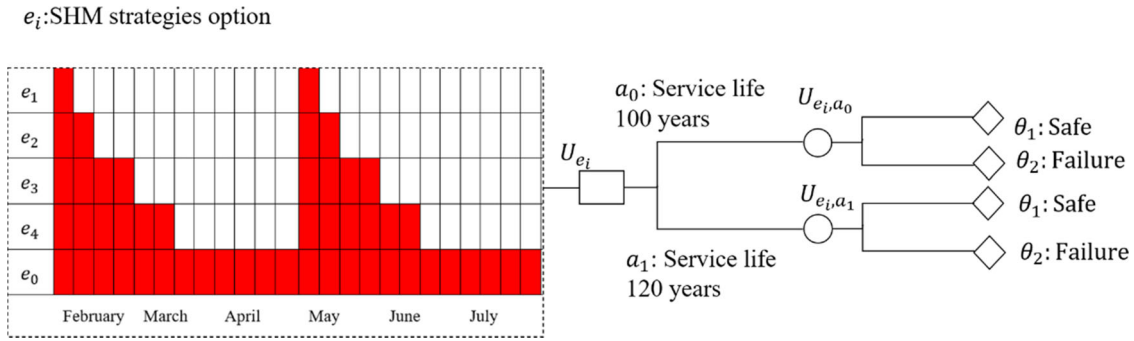


Figure 8. Decision tree of posterior decision analysis.

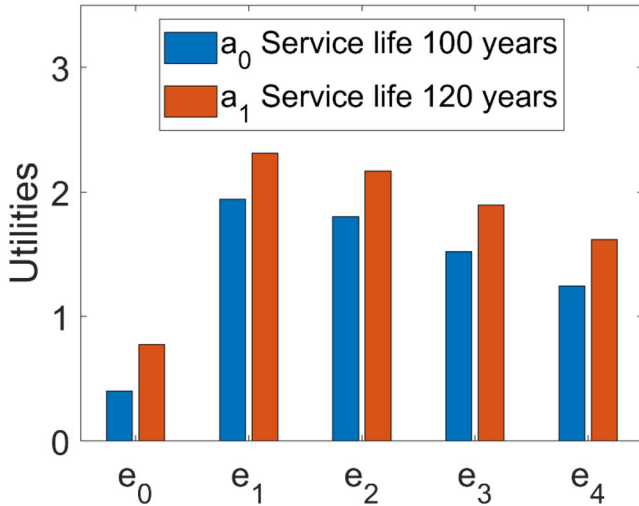


Figure 9. Identification on the most valuable SHM strategies during the bridge service life.

benefit, C_F is the failure cost and C_R is the planned rehabilitation cost (in relation to Equation (2), repair costs C_R and inspection costs C_I are taken together in the case study and presented as rehabilitation cost C_R); t_R is the year of rehabilitation; C_M is the cost of monitoring per day; N_{m, e_i} is the total monitoring days from strategy e_i ; N_{R, a_j} is the total number of repair times with action a_j ; t_m is the year of monitoring. γ is the discounting rate.

From the literature (Sund & Bael, 2014), it is known that the Great Belt bridge and the connected tunnel, roads and railways together are called the Storebaelt link, which was built between 1988 and 1998, with the total construction costs amounting to EUR 3.56 billion in 1988 prices. The construction costs are financed through the state guarantee model and the loans are repaid by the users of the facilities. It is found that the Great Belt Company had loans guaranteed by the government and lent capital at an interest rate of 1.5-2% (Mouter, 2015). According to the report released by the Ministry of Transport and Sund & Bael (2014), it is revealed that the Storebaelt link would bring a gain of EUR 50.87 billion over 50 years to Danish society, equivalent to EUR 1.21 billion annually, while the construction and operation of the link over a 50 year period costs just EUR 18.66 billion.

Based on the information above, to illustrate the case study, it is assumed that half of the gain from the Storebaelt

link comes from the Great Belt bridge, so that the normalized annual benefit B for the Great Belt bridge is 0.17 ($0.5 * 1.21 / 3.56$) per year, the normalized cost of rehabilitation C_R is 5 ($18.66 / 3.56$), the normalized cost of failure C_F is assumed to be 100, the normalized cost of monitoring C_M is assumed to be 0.01 per day, the discounting rate γ is 0.02 (equivalent to interest rate) per year. It is noted that due to the confidentiality, the data shall be read as an illustration of the input parameters of the presented methodology, and not as representative of the actual cost and benefits of the Great Belt bridge.

3.6. Results

The utility calculation follows Section 3.5 and the results are shown in Figure 9. The findings in Figure 9 indicate that for all SHM strategies it is recommended to extend service life to 120 years. The utilities in Figure 9 show that option e_1 will be recommended due to the highest utility. It is found that in the case study a long monitoring duration will reduce the risk but increase the cost of monitoring, which leads to an overall reduction in utility. The additional cost of longer monitoring is not justified here because the reduction of risk does not compensate for the increase of the cost. The optimal SHM strategy is thus short-term monitoring. However, the results may be sensitive to the variation of cost and benefit models, which is investigated in Section 4.

4. Parametric analysis

Further to the results presented in Figure 9, due to the uncertainties related to the input parameters, a parametric analysis of the utilities associated with different monitoring durations and choices of actions is performed considering the variability of the model parameters: (a) target probability P_{Target} , (b) benefit B , (c) failure cost C_F , (d) rehabilitation cost C_R , (e) monitoring cost C_M and (f) discount rate γ .

4.1. Target probability P_{Target}

The target probability P_{Target} is the acceptable optimum failure probability which is known as an adaptive control parameter based on the degree of failure impact and the relative expense of protection measures (JCSS, 2001). It varies from 10^{-6} (large consequences of failure, small

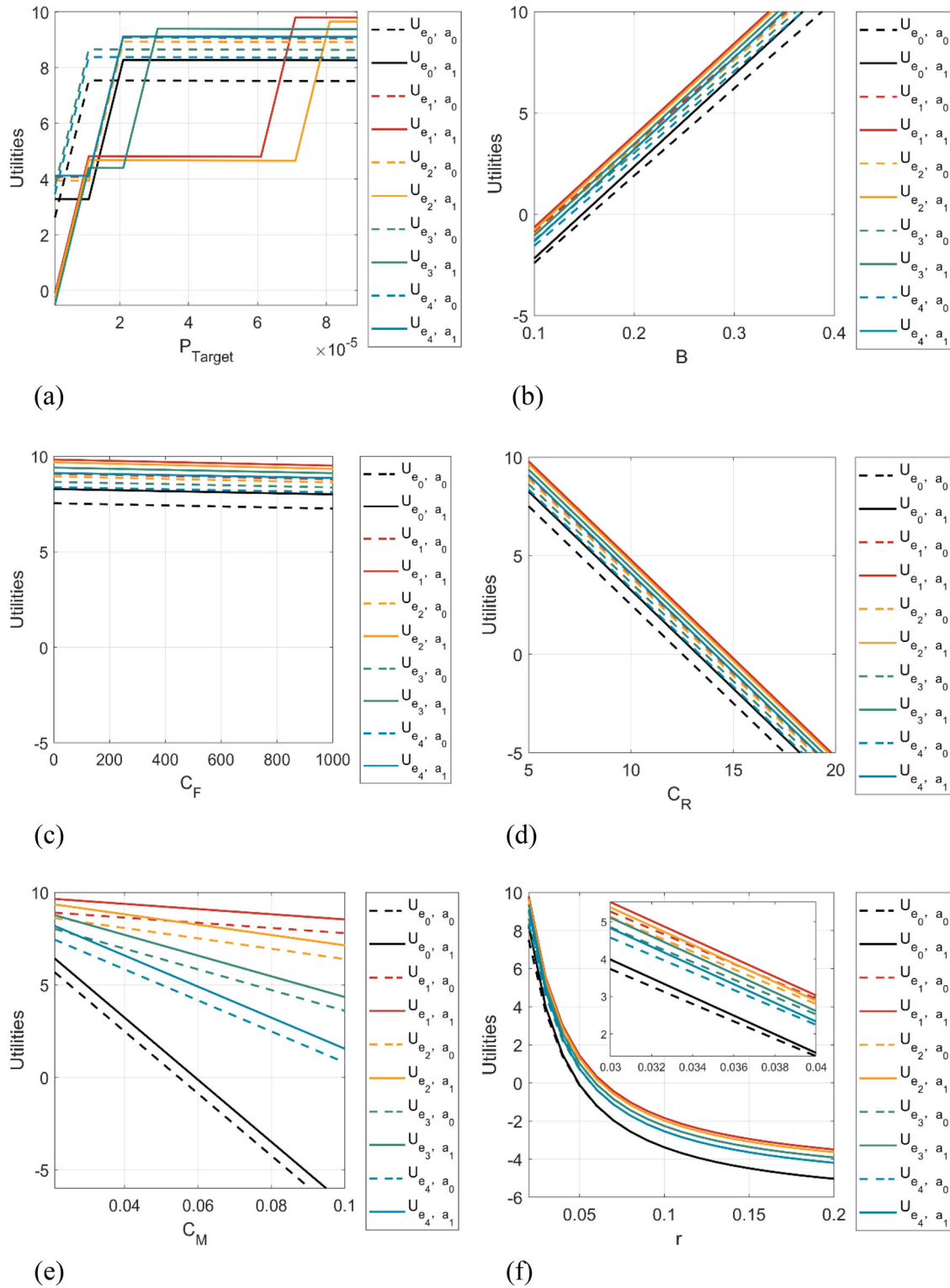


Figure 10. utilities associated with different monitoring durations and choices of actions considering the variability of the model parameters: (a) target probability P_{Target} , (b) benefit B , (c) failure cost C_F , (d) inspection and rehabilitation cost C_R , (e) monitoring cost C_M and (f) discount rate γ .

relative cost of safety measures) to 10^{-3} (minor consequences of failure and large relative cost safety measure) according to (JCSS, 2001). The target probability P_{Target} was previously chosen as 10^{-4} considering minor consequences of failure and a normal relative cost of safety measures. For assessing its effect, it is reduced from 10^{-4} to 10^{-5} and the outcomes are shown in Figure 10(a). Reducing the target

probability means that decision-makers are more conservative with lower tolerance of risk leading to the welds being rehabilitated more often during service life.

Figure 10(a) presents the utilities with the abovementioned change. The utilities are all increasing with the increase of the target probability. It increases linearly in some ranges but stays constant in other ranges. The utilities

Table 4. Summary of the most valued decisions about the SHM strategy to adopt, regarding the critical parameters.

Critical parameter	Most valued decision
Target probability, P_{Target}	For $P_{Target} < 2 \cdot 10^{-5}$, monitoring for 4 consecutive weeks every 6 months, given the service lifetime is kept to 100 years (e_3, a_0) For $2 \cdot 10^{-5} \leq P_{Target} < 3 \cdot 10^{-5}$, monitoring for 6 consecutive weeks every 6 months, given the service lifetime is extended to 120 years (e_4, a_1) For $3 \cdot 10^{-5} \leq P_{Target} < 7 \cdot 10^{-5}$, monitoring for 4 consecutive weeks every 6 months, given the service lifetime is extended to 120 years (e_3, a_1) For $P_{Target} \geq 7 \cdot 10^{-5}$, monitoring for 1 week every 6 months, given the service lifetime is extended to 120 years (e_1, a_1)
Benefit, B	Monitoring for 1 week every 6 months, given the service lifetime is extended to 120 years (e_1, a_1)
Cost of failure, C_F	
Cost of rehabilitation, C_R	
Cost of monitoring, C_M	
Discounting rate, γ	

curves of options e_1 and e_2 with action a_1 behave differently from the other curves. They start at the lowest value but end the highest values at the highest target probabilities. That's because options e_1 and e_2 provide higher probability of failure than others. Hence, when P_{Target} is high, options e_1 and e_2 will reach the target probability earlier, thus resulting in more times of rehabilitation when reaching 100 years (a_0). To compensate the increase of the rehabilitation costs, it will be suggested to continue operation to 120 years (a_1). Their flat plateau is however significantly lower than the plateaus of the other curves. The a_0 action is more consistent with longer constant flat plateau over almost all of the observed range. For a low value of P_{Target} , all options except e_1 and e_2 have very similar utility values.

There are certain thresholds for P_{Target} where sudden increases of the utilities occur. When $P_{Target} < 2 \cdot 10^{-5}$, option e_3 with action a_0 has the highest utility. When

$2 \cdot 10^{-5} \leq P_{Target} < 3 \cdot 10^{-5}$, utility with option e_4 and action a_1 is the highest. When

$3 \cdot 10^{-5} \leq P_{Target} < 7 \cdot 10^{-5}$, utility with option e_3 and action a_1 is the highest. When $P_{Target} < 2 \cdot 10^{-5}$, option e_1 with action a_1 will be recommended. A summary of most valued decisions with changed of P_{Target} can be found in Table 4. The summary of utilities in Figure 10(a) shows that the change of the target probability actively affect the decision of optimal SHM durations and service life extension of the welds. The tolerant- to- risk decision maker (high value of P_{Target}) will get more benefit with the change on the P_{Target} .

4.2. Benefit B

The annual benefit is subjective to change due to the growth of population, change of urban planning etc. Therefore, the annual benefit rate B is increased and the results are shown in Figure 10(b). It is found that e_1 has the highest utilities and the utilities associated with a_1 extending service life to 120 years are always higher than those with a_0 . This is because of a higher profit-drive leading to a longer operation period. Figure 10(b) shows that the utilities increase linearly with the increase of benefit, but the difference between the slope of curves of the varied monitoring durations is very small.

4.3. Cost of failure C_F

When increasing the cost of failure C_F from 100 to 1000, the computation results in Figure 10(c) display the same trend as in Figure 9 leading to the extension to 120 years (a_1) with option e_1 . The utilities are slightly decreasing with the increase of C_F . The choice of the service life extension and choice of monitoring duration are not influenced much by the change of cost of failure. It is because the difference between the utilities for 120 years and 100 years is the same. It is also due to the very small annual probability of failure, the accumulated risk of failure is comparably small as well.

4.4. Cost of rehabilitation C_R

The cost of rehabilitation may be subject to change due to the choice of rehabilitation methods. When increasing the cost of rehabilitation C_R from 5 to 50, the utilities in Figure 10(d) strongly decrease and become negative for both keeping the service life at 100 years a_0 and extending it to 120 years a_1 . That is because the accumulated benefits and reduction of risk of failure cannot compensate the increase of cost of rehabilitations when the rehabilitation cost is too high. The variations between the maximum utilities of all the options in Figure 10(d) are very small. It can be interpreted that when the cost of rehabilitation is very high, it is no longer worthwhile to investigate the SHM strategies, which is not competitive, but the focus should be on finding solutions to reduce the cost of rehabilitations.

4.5. Cost of monitoring C_M

The cost of monitoring may differ based on the choice of monitoring techniques. When increasing the cost of monitoring C_M from 0.01 to 0.1 per day, Figure 10(e) shows that it is not beneficial to do monitoring with reference SHM option e_0 due to high monitoring costs. As expected, the utility decreases with increasing monitoring durations, but the decreasing gradient is different. The curve of option e_1 has the lowest gradient. Therefore, it is recommended to do monitoring with option e_1 and extend the service life to 120 years. A decision-maker could learn that the sparser and shorter the SHM campaigns, the better is the payback of monitoring and lesser its sensitive to the SHM cost.

4.6. Discounting rate γ

The discount rate is also connected with the so-called social discount rate, which represents the value that society assigns to its existing situation compared to potential future states. It has significant variations in practice around the world (Zhuang, Liang, Lin, & De Guzman, 2007), with lower levels introduced by developed countries (3%-7%) than the developing countries (8-15%). The value of discount rate also changes with time depending on public policies, e.g., the Danish Ministry of Finance in May 2013 reduced its social consumption discount rate from 5% per year to 4% per year for the first 35 years for the investment of long-term projects, 3% for the years in the interval 36 to 69 years, and 2% for the rest of years (Finansministeriet, 2013).

The discounting rate γ is increased from 0.02 to 0.2 and the results in Figure 10(f) illustrate that the utilities are exponentially decreasing and option e_1 has the highest utilities. The utilities of keeping 100 years a_0 or extending to 120 years a_1 have almost the same value. When the discounting rate γ is larger than 0.05, the utilities become negative. That's because a higher discount rate means greater uncertainty and the cash flow in the future will have a lower value. Since money loses value fast with time, it is not beneficial to invest on long-term return projects. Thus it may be recommend not to invest in monitoring at all when the discounting rate γ is high. A decision-maker could learn that the longer is the implementation of the SHM strategy, the higher the importance of the economic situation of the country.

5. Conclusions

Many studies focus on SHM data gathering, processing and probabilistic model developing. Building upon these studies, this article contains methodology to utilize the obtained monitoring information for the determination of i) optimal monitoring durations and ii) service life extension of the welds on a steel bridge deck. Through a posterior utility-based decision analysis of the welds on an orthotropic steel bridge deck case study, it is shown that a short-term SHM strategy has a higher expected utility and is thereby preferred. In contrast, long-term monitoring duration reduces the risks but leads to an increase of the monitoring costs, which in turn leads to an overall reduction in the expected utility.

Through a parametric analysis, this article shows how the target probability P_{Target} , benefit B , failure cost C_F , rehabilitation cost C_R , monitoring cost C_M and discounting rate γ influence the expected value of the utility and thus the decisions:

- It is found that the target probability P_{Target} is the most sensitive parameter as the change of P_{Target} will directly change the number of rehabilitation times and the posterior probability of failure, thus change the total expected rehabilitation costs and the accumulated risk of failure, resulting in different choices of monitoring

options and service life extension. However, P_{Target} may be subjected to optimization in conjunction with the risk attitude of the decision makers. The tolerant- to-risk decision maker (high value of P_{Target}) will get more benefit with the change on the P_{Target} .

- An increase of annual benefit B will lead to service life extension. A higher profit-drive will lead to a longer operation period.
- SHM strategies become not competitive (i.e., not worthwhile) when the cost of rehabilitation is too high. The rehabilitation methods should be chosen carefully as a high rehabilitation cost C_R results in negative utilities.
- An increase of monitoring cost C_M will result in a short-term monitoring option. The sparser and shorter the SHM durations, the better is the payback of monitoring and lesser its sensitive to the SHM cost.
- For the investment in monitoring, the discounting rate γ should be thoroughly considered, as a high discounting rate γ will lead to significantly declining utilities. In such a case, investing in long-term ventures is not advantageous and short-term returning investment is more beneficial. The longer is the implementation of the SHM strategy, the higher the importance of the economic situation of the country.

The presented research work considers solely the fatigue reliability and service life management of selected welds on an orthotropic steel bridge deck. Future research is needed to investigate the problem on a system level. Moreover, due to the methodology specificities, several assumptions on fatigue life prediction have been made and normalized cost and benefits models used. This highlights that the results presented in the article shall be read as an illustration of the presented methodology for assessing optimal monitoring strategies, and not necessarily as the actual fatigue life of the instrumented details and not as representative of the actual cost and benefits of the Great Belt bridge. Future research is envisaged to explore comprehensive probabilistic formulations of cost and benefit function and fatigue life prediction model considering not only a single sloped SN curve.

Notations list

$u(e, z, a, \theta)$	Utility function
e	The SHM strategy/experiment
z	The SHM /experiment outcome
a	Action
θ	System state
$P(e, z, a, \theta)$	Probability of the state of the structure θ after implementing a strategy e , obtaining the outcome z and taking an action a .
$U(e, z, a, \theta)$	Expected utility function
U_{SL}	Expected utility during service life
U_B	Expected benefit
U_F	Expected cost of failure
U_R	Expected cost of repair
U_I	Expected cost of inspection
U_M	Expected cost of monitoring
$B(t)$	The annual benefit at year t
$C_F(t)$	The cost of failure at year t
$C_R(T_i)$	The cost of repair at repair year T_i
$C_I(T_j)$	The cost of inspection at inspection year T_j

$C_M (T_m)$	The cost of monitoring at monitoring year T_m
T_i	The repair year
T_j	The inspection year
T_m	The monitoring year
N_R	The total number of repair
N_I	The total number of inspections
N_M	The total number of monitoring
$P(F_t)$	The probability of failure at year t .
$\Delta P(F_t)$	The annual probability of failure at year t
$P(R_{T_i})$	The probability of repair at repair year T_i
T_{SL}	The service life
γ	The discounting rate
P_{Target}	The target probability
$D_{\Delta t}$	S-N fatigue loading aggregated during a time interval Δt
$B_{\Delta t}$	Daily aggregated counts of daily vehicles
$T_{\Delta t}$	Daily averaged pavement temperature
s_{tot}	Estimator of the total variance of a regressing model
T_0	Given pavement temperature
n	Number of available datapoints
p	Order of a polynomial regression model
t_{n-p-1}	t-probability distribution with n-p-1 degrees of freedom
Δ	Miner's sum at failure
A	Material parameter defining the SN fatigue curve.

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