Title: **Quantification of the posterior utilities of SHM campaigns on an orthotropic steel bridge deck**

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ABSTRACT

This paper contains a quantification and decision theoretical optimization of the posterior utilities for several options for monitoring campaigns on the particular case of fatigue life predictions of an orthotropic steel deck. The monitoring campaigns are defined by varying monitoring durations and phases. The decision analysis is performed with real data from the Structural Health Monitoring (SHM) of the Great Belt Bridge (Denmark) which, among others, consist of measured strains, pavement temperatures and traffic intensities. The fatigue loading prediction model is based on regression models linking daily averaged pavement temperatures, daily aggregated heavy-traffic counts and derived S-N fatigue damages, all of them derived from the outcomes of different monitoring campaigns. A probabilistic methodology is utilized to calculate the fatigue reliability profiles of selected instrumented welded joints. The posterior utilities of SHM campaigns are then quantified by considering the structural fatigue reliability, various monitoring campaigns and the corresponding cost-benefit models. The decisions of identifying the optimal monitoring campaign and of extending the service life or not in conjunction with monitoring results are modelled. The optimal monitoring campaign is identified - retrospectively - by maximizing the expected benefits and minimize risks in dependency of the monitoring duration and the monitoring associated costs. The results, despite relying on a number of simplistic assumptions, pave the way towards the use of pre-posterior decision support to optimise the design of monitoring campaigns for similar bridges, with an overall goal to proof the cost efficiency of SHM approaches to civil infrastructure management.

INTRODUCTION

Structural health monitoring (SHM) is widely used in all kinds of structures [1]. However, neither the value of SHM in general nor the discussion regarding the selection

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of optimal monitoring durations are normally addressed in quantitative terms. In many cases, SHM systems are designed and installed based on engineering judgement and experience, rather than on cost-efficiency considerations. Only recently it has been acknowledged that the benefits of SHM can be quantified utilizing the concept of value of information [2–5]. In this regard, reference [6] presented through quantifying the value of SHM, that a highly industrial potential for substantial increased life cycle benefits can be obtained. The above was also proved in [7] through quantifying the conditional value of SHM data for the fatigue safety evaluation of a road viaduct. Moreover [8, 9] found that sensor configuration can be optimized through the dynamic value of damage detection system information analysis. The present paper focus on optimizing SHM strategies in terms of monitoring duration and phases. This is done through the posterior decision analysis [10], which quantifies how much utilities can be achieved through improving life- cycle integrity management based on obtained SHM information. By comparing the posterior utilities of different SHM campaigns, the optimal strategy can be determined. The above is illustrated with data from the Great Belt Bridge (Denmark), which is used to derive different models for predicting remaining fatigue life.

The Great Belt Bridge is a suspension bridge in Denmark starting operation from 1998, with main span of 1624m and maximum hanger length of 177m (Figure 1). Its cross-section is formed by a closed steel box girder with an orthotropic steel bridge deck (OSD), formed by the longitudinal troughs and cross-beams spaced every 4 m. Extensive fatigue analysis have been carried out to determine the fatigue life of selected welds of its orthotropic steel deck such as the welds between the deck plate and the trough stiffeners and at the trough splices. The designed fatigue life for the orthotropic welds was 100 years with different inspection interval for different weld details.

In 2007, after ca. 10 years of operation, an extensive Structural Health Monitoring system was installed on the bridge, recording simultaneously strains at selected welded joints of the OSD and pavement temperatures for design verification. Traffic intensities have been captured at the toll system since bridge commissioning. The monitoring data was used to develop data-based models [11] and the fatigue life of OSD welded joints was estimated through a probabilistic methodology in [12]. The monitoring data was divided into different data sets in [13] to predict the fatigue life of OSD welded joints through the probabilistic methodology described in [12]. Following the research results in [11], this paper addresses 1) the quantification of the posterior utilities of the different monitoring campaigns defined in terms of different durations, 2) the presentation of a theoretical framework relying on a number of simplifying assumptions to solve the decision problem on whether to extend the fatigue service life of the welds or not through development of a new maintenance strategies within life-cycle asset integrity management and 3) the determination of optimal monitoring strategies in terms of the number of monitoring phases, durations and intervals to predict fatigue life on OSD welded joints.

SHM PROBABILISTIC FATIGUE MODEL

The SHM system on the Great Belt bridge consists, among others, of pavement temperature monitoring system, traffic monitoring system (used by the toll system) and strain monitoring system. Four temperature monitoring sensors are embedded into two

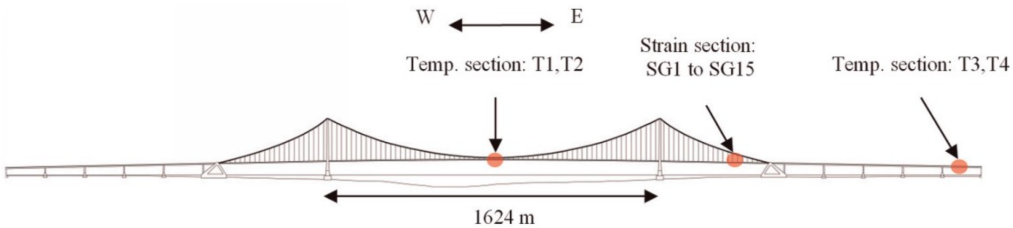

Figure 1. Illustration of Great Belt Bridge.

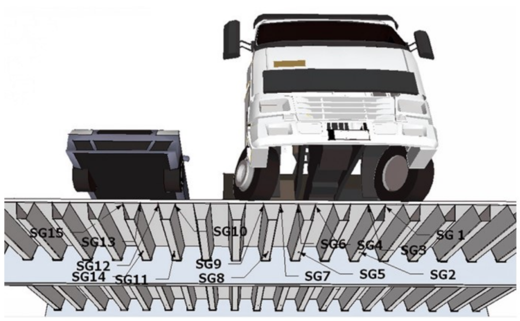

Figure 2. Illustration of Illustration of monitoring system

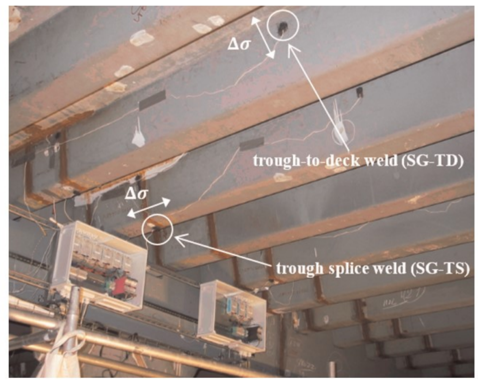

Figure 3. Strains gauges at welds

different cross-sections of the pavement and record the temperature every 5 minutes. The crossing vehicles are automatically classified according to their dimensions at the toll system on an hourly basis. The strain monitoring system instrumented in a cross-section, consisting of 15 uniaxial strain gauges (Figure 2), in which 10 gauges (i.e. 1,3,4,6,7,9,10,12,13,15) monitor the transverse nominal strains at the through to deck weld, and 5 gauges (i.e. 2,5,8,11,14) monitor the longitudinal nominal strains at trough splice welds (Figure 3). Strain gauges 1to 9 are placed under the slow traffic lane which pass by the heavy vehicles, whereas the rest are placed under the fast traffic lane.

A probabilistic methodology was introduced in [11] to calculate the fatigue reliability profiles of monitored welded joints, based on a succession of regression and time-series models considering daily averaged pavement temperatures, daily aggregated heavy-traffic and associated S-N fatigue damages conservatively calculated by considering single-sloped S-N curves and following Miners accumulation rule. The fatigue limit state function associated with the above is [11, 12]:

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

where t is time, X is the vector of random variables, Δ is the Miner's sum at failure, A is the material parameter defining the SN fatigue curve, $B_{\Delta t}(t)$ is the daily-aggregated heavy traffic counts, $T_{\Delta t}(t)$ is the daily averaged pavement temperatures, θ is the parameters of the regression models, n is the number of data points corresponding to the training data set associated with the regression mode, p is the order of the regression model,

t_{n-p-1} is a t-distribution with $n-p-1$ degrees of freedom and s_{tot} is the estimate of the total variance of the regression model at a given $T_{\Delta t}(t)$. The weld will fail when the accumulated fatigue damages is larger than the Miners sum at failure. So that the probability of failure can be modeled through Monte Carlo Simulation as:

$$P(F) = P(g\,(x, t) \leq 0) \tag{2}$$

The variables in the probabilistic model are simulated following the model described in Table I. Apart from considering the S-N fatigue parameter and Miner's sum at failure as random variables not linked with SHM data, SHM data is used to derive 3 different models for fatigue 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 Eq.1, 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 prediction of fatigue life of all the welds under monitoring of the strain gauges is presented in [12]. The probability of failure of welds will increase with time. In this paper, it is assumed that when reliability profiles reach a certain target probability, it is required to take action. In [12] it is pointed out that the SG8 (measured the trough splice weld) will reach the target reliability first. This behavior can be easily explained as this weld is under the slow traffic lane where heavy vehicles run inducing higher stress cycles than at the fast lane. The discussion of SHM campaigns in the following is based on the training data sets from SG8. The reference monitoring option consists of the data set between February 2012 to July 2012, which is assumed to capture the complete temperature range within a typical year due to the annual repeatability of the pavement temperature distribution [13]. According to the different number of monitoring phases and time duration per phase, four different monitoring strategies in terms of time durations are discussed as shown in Table II. We chose the target probability as 10^{-4}(β=3.7) according to [15] considering normal relative cost of safety measure and minor consequences of failure. For the purpose of this paper, the weld is assumed to get rehabilitation after reaching the target probability. It is also worth noting that the fatigue reliability profiles are very conservative given the consideration of single-slopped S-N curves with no cut-off limit. The above assumptions highlight the fact that the results presented in the paper shall be read as an illustration of the presented methodology for assessing optimal monitoring strategies.

QUANTIFICATION THE POSTERIOR UTILITIES OF SHM CAMPAIGNS

TABLE I. VARIABLES OF THE PROBABILISTIC MODEL

Parameter	Symb	Distribution/Expression
Trough-to-deck weld fatigue parameter	A	LN(7.30E11, 4.23E11) [14, 15]
Trough-splice weld fatigue parameter	A	LN(2.09E12, 1.21E12) [14, 15]
Miner's damage at failure	Δ	LN(1.0,0.3) [16]
Daily heavy traffic counts	$B_{\Delta t}(t)$	Time series model from[11]
Daily-averaged pavement temperatures	$T_{\Delta t}(t)$	Time series model from[11]

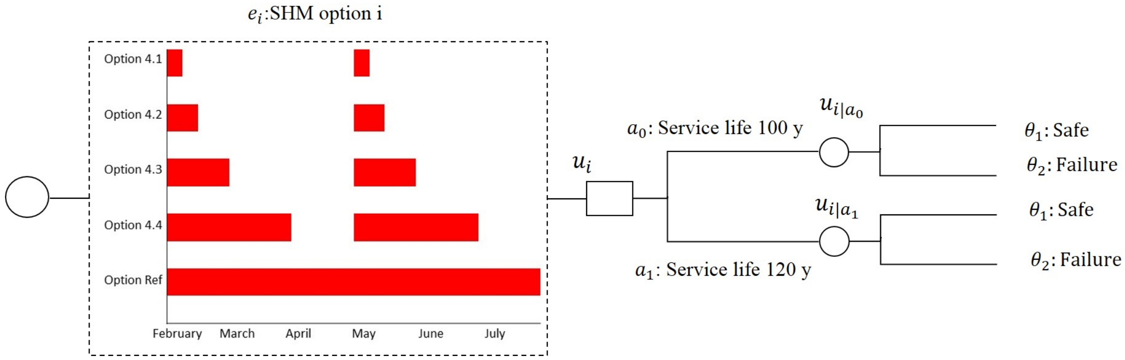

Figure 4. Illustration of decision tree of posterior decision analysis.

In this paper, we want to investigate whether to extend the service life to 120 years or stay to 100 year. Given that different monitoring campaigns will provide different predictions of fatigue reliability profiles, we also want to know which monitoring campaign can achieve maximum utilities/benefits for the life-cycle integrity management. A posterior decision analysis is introduced to solve the problem. This is done by considering the fatigue reliability profiles, various monitoring scenarios as well as the corresponding cost-benefit models. The illustration of the decision tree process is shown in Figure 4 with a_i denoting the choice of the actions such as a_0 for a service life of 100 years and a_1 to extend service life to 120 years. For different choice of the service life, the integrity of the welds needs to be managed causing planned rehabilitation costs C_R. The states of the welds θ_i are defined as θ_1 safe and θ_2 failure. It will fail when the accumulated fatigue damages are larger than Miners damage at failure. If the weld stays safe, the bridge will be operated normally with annual benefits B. If the weld fails, unscheduled repair events will be required, so that and there will be a fatigue failure costs C_F which will be the sum of the unscheduled repair costs and the costs of interrupting normal traffic during repair activity. e_i represents the different information strategies, for example e_0 denotes reference SHM campaigns, e_1 doing SHM with option 4.1, etc. Considering different monitoring phases, monitoring duration and period, there will be a different cost of monitoring C_M. We use u_i to present the expected maximum utilities regarding different actions under different strategy information.

$$u_i = \max[u_{i|a_0}, u_{i|a_1}] \tag{3}$$

The utility branches when staying service life for 100 years with SHM $u_{i|a_0}$ are calculated:

TABLE II. SHM CAMPAIGNS

Option	Number of monitoring phase	Time duration per Phase [days]	Total duration [days]	Percentage data used: %
Ref	1	168	168	100
4.1	2	7	14	8.3
4.2	2	14	28	16.6
4.3	2	28	56	33.3
4.4	2	42	84	50

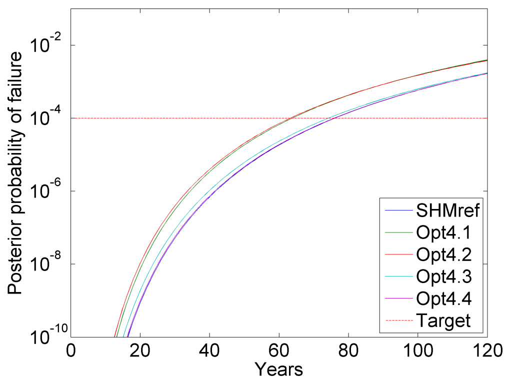

Figure 5. Prediction of probability of fatigue failure during service life of 120 years and with target probability

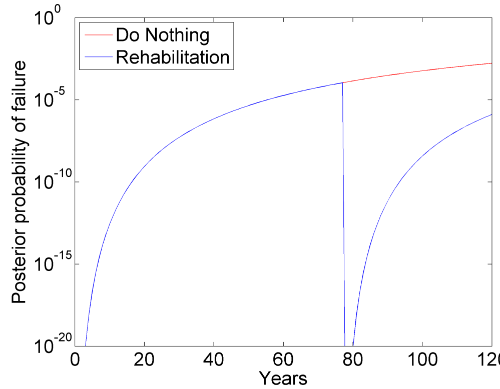

Figure 6. Probability of fatigue failure if doing nothing or rehabilitation given reference SHM data

$$
\begin{aligned}
u_{i|a_0} = \sum_{T=1}^{T_{SL|a_0}} (1 - P\left(F|M_{e_i}\right)) B \frac{1}{(1+\gamma)^T} - \sum_{T=1}^{T_{SL|a_0}} P\left(F|M_{e_i}\right) C_F \frac{1}{(1+\gamma)^T} \\
- \sum_{N=1}^{N_i} C_M \frac{1}{(1+\gamma)^{T_M}} - \sum_{N=1}^{Na_0} C_R \frac{1}{(1+\gamma)^{T_R}}
\end{aligned}
\tag{4}
$$

In Eq.4, B is the benefit, C_F is the cost of failure, C_R is the cost of planned rehabilitation which is dependent on the number of rehabilitation times Na_0 during 100 years of service life and discounted to the year of rehabilitation T_R. C_M is the cost of monitoring which is dependent on total monitoring duration N_i and discounted to the year of monitoring T_M. γ is discounting rate, $P\left(F|M_{e_i}\right)$ is the posterior probability of failure given monitoring during service life. The utility branches when extending service life to 120 years with SHM $u_{i|a_1}$ are calculated as:

$$
\begin{aligned}
u_{i|a_1} = \sum_{T=1}^{T_{SL|a_1}} (1 - P\left(F|M_{e_i}\right)) B \frac{1}{(1+\gamma)^T} - \sum_{T=1}^{T_{SL|a_1}} P\left(F|M_{e_i}\right) C_F \frac{1}{(1+\gamma)^T} \\
- \sum_{N=1}^{N_i} C_M \frac{1}{(1+\gamma)^{T_M}} - \sum_{N=1}^{Na_1} C_R \frac{1}{(1+\gamma)^{T_R}}
\end{aligned}
\tag{5}
$$

In Eq.5, the number of planned rehabilitation times Na_1 will be changing corresponding to 120 years of service life. The posterior probability of failure after monitoring $P\left(F|M_{e_i}\right)$ is calculated following the probabilistic fatigue model shown in Figure 5. The posterior probability of failure if doing nothing or after rehabilitation given reference SHM data is shown in Figure 6. Assuming the normalized benefit B is 20 per year, the cost of failure C_F is 100, the cost of rehabilitation C_R is 200, the cost of monitoring C_M is 0.5 per day, the discounting rate γ is 0.02 per year, the calculation results are

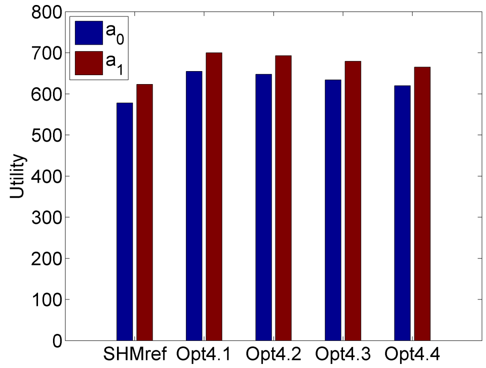

Figure 7. Posterior utility calculation between two choice of actions among different SHM campaigns

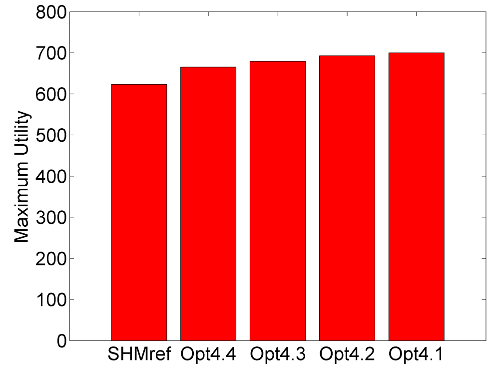

Figure 8. Maximum posterior utilities between two choice of actions among different SHM campaigns

shown in Figure 7. In all cases it is recommended to extend service life to 120 years with monitoring. The summary of utilities in Figure 8 shows that option 4.1 will be recommended due to the highest utility. In this case, 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 here not justified because the risk decrease does not compensate for the increase of the cost. The optimal SHM strategy is thus short-term monitoring. However, the results can be sensitive to the variation of cost and benefits models, which needs to be further investigated.

CONCLUDING REMARKS

This paper provides an approach to optimize monitoring strategies through the quantification of the posterior utilities of different monitoring campaigns. This paves the way towards the use of pre-posterior decision support to optimize the design of monitoring campaigns for similar bridges, with an overall goal to maximize the expected benefits and minimize the risks throughout the service life of structures. However, this paper only considers the fatigue reliability and life cycle management of welds. Future research could investigate the fatigue reliability of the system level as well as the need for probabilistic formulations of the cost function. Similarly, application-specific cost functions should be strengthened and how to do a pre-posterior decision analysis even before the implementation of SHM should be discussed in the future.

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