The 6th International Conference on
Structural Health Monitoring of Intelligent Infrastructure
Hong Kong | 9-11 December 2013

BAYESIAN UPDATING OF MARINE STRUCTURAL RELIABILITY MODELS BASED ON IN-SERVICE MEASUREMENTS

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ABSTRACT

Estimating future reliability and maintenance needs of aging ship structures is a growing challenge. It is attractive to use structural health monitoring data to forecast future structural conditions via a model updating approach. A unique challenge in model updating for ships is their inherent mobility, which subjects them to different environments and operational profiles at different points in their service lives. Thus, updating and forecasting techniques must not only be able to track the type of usage experienced to date, but also potentially forecast future performance in different conditions. This paper explores a model updating approach concentrating on structural fatigue failures, examining both seaway load and fatigue capacity updating. In seaway load analysis, the loads experienced by the vessel are calculated in a series of operational cells corresponding to unique combinations of sea state, heading, and speed. Lifetime loading profiles are then constructed through probabilistic integration of these individual cells. A cell-based updating strategy is presented where Markov Chain Monte Carlo methods are used to approximate model bias and uncertainty factors by comparing predicted loads to experienced loads in cells observed to date. The errors are estimated and used to forecast updated loads in unobserved cells, leading to a refined prediction of lifetime loading. The fatigue capacity updating model uses a lognormal modelling approach to calculate and analyze the probability of crack initiation time and associated reliability. This model is extended to via efficient formulas for forecasting the expected number of fatigue cracks over time in grillage-type structures with multiple similar fatigue-prone details. A Bayesian network is used to develop revised capacity parameter estimates and estimates of future rates of fatigue cracking through an inference approach-based method on observed failures and updated loading data. Examples are provided to show the updating power of this approach and a simple method of combining the two updating approaches.

KEYWORDS

Structural health monitoring, Bayesian updating, Bayesian network, reliability modeling, lifetime load assessment.

INTRODUCTION

Marine structures, such as ships and mobile offshore platforms, operate under uncertain service lives. It is often desirable to extend the structure's service life beyond the initially planned life based on economic or operational constraints. For example, in the public sector, shrinking acquisition budgets and delays in the development of new-generation vessels has caused a need for extending the service lives of many naval and coast guard vessels around the world. At the present time, such service life extension decisions are normally made with only rough estimates of future structural safety, repair costs, and potential system downtime for maintenance. Better prognosis of future structural states and associate safety, cost, and downtime would allow improved service-life extension decisions. With the present growth in the capacity to sense both environmental conditions as well as structural responses in structural health monitoring (SHM) systems, updating design-stage structural models for future prognosis is increasingly attractive.

The problem of sensing and performing model updating on marine structures has been well studied over the past decade. Like much of the SHM community, initial developments focused primarily on the ability to efficiently sense the response of spatially large and complex structures (Baldwin et al. 2002; Swartz et al. 2012; Silva-Muñoz and Lopez-Anido 2009; Sielski 2012). More recently, several authors have proposed frameworks for interpreting SHM data and updating underlying performance models. Salvino et al. (2009) proposed a multi-tier framework for integrating SHM readings and prediction models for naval vessels. The ability to process the

large amount of data generated by SHM systems and intelligently update models continues to be an active area of development for the marine community. Extending the initial work of Salvino et al., a data-to-decision framework has recently been presented for marine structures (Collette and Lynch 2013). This approach relies in part on technologies developed in the civil engineering world for bridge health management, demonstrating that there are common challenges in integrating SHM data across application disciplines. In a similar vein, the Frangopol research team at Leigh has been adapting approaches pioneered for time-dependent bridge inspection, maintenance, redundancy and cost optimization to ship structures (Decò, Frangopol, and Zhu 2012; Frangopol et al. 2012; Okasha, Frangopol, and Decò 2010). Notably, the work of Frangopol's group also integrates reliability-based measures, paralleling efforts in the wider marine structure community to adopt reliability-based structural design approaches for marine structures.

The present work focuses on the problem of updating a probabilistic structural fatigue cracking model for marine structures. Fatigue failures are a major concern, particularly for ship structures where cyclical loading on the hull results in primary stresses that alternate between tension and compression. Such full stress reversals are uncommon in physically large structures (Beach 2012). Often 10^7 to 10^8 loading cycles are experienced in a vessel's service life, making structural fatigue a primary maintenance concern. A two-stage updating model is presented in this work to allow for a future prognosis of fatigue failures. The fatigue capacity of the structure is modelled using a probabilistic lognormal model, which allows for an efficient prediction of the probabilities of fatigue failures occurring over time. This model is updated via a Bayesian network based on observed failures, which are then used to predict future failures.

While the Bayesian network approach can update both capacity and loading based on observed failures, the mobility of most marine structures suggests that a different approach should be taken. The environmental loading of marine structures may not be statistically stationary over the course of the vessel's life. Changes in operational environment owing to new trade routes (e.g. the open of the Arctic) may change the environmental conditions that the structure is exposed to, while changes in the freight market and fuel prices may change the speed at which the owner chooses to operate the vessel. Both environment and speed can significantly impact the loads experienced by the structure. Likewise, changes in the geo-political situation for military ships can result in entirely new loading being applied to their structure. If loading is assumed stationary and past loading is used to update models for future state prognosis, these factors would be missed. Instead, an approach is proposed where the underlying loading model is updated based on errors between measured and predicted responses in observed conditions. This updated loading model can then be used to predict future loading in potentially unobserved conditions. The remainder of this paper presents these updating approaches, the fatigue capacity model and the updating approach, followed by the load prediction model updating approach. Results are then shown for the capacity model and load prediction model alone. A combined example of updated loads and capacity based on both models simultaneously is presented, followed by conclusions.

METHOD OF SOLUTION

Fatigue Model

The fatigue capacity model uses a log-normal modelling approach to solve the crack initiation reliability problem analytically, inspired by Wirsching (1984). A simple fatigue model is proposed, based upon a probabilistic interpretation of the classical S-N fatigue approach extended by the Palmgren-Miner variable amplitude fatigue characteristic (Collette 2011). In this approach, the number of cycles to fatigue crack initiation at a given structural location is determined to be an S-N equation below, where A and m are experimentally-determined constants, $\Delta\sigma$ is the equivalent stress range acting on the fatigue location, k_f is a stress modelling uncertainty factor, and D_{cr} is the cumulative damage index from the Palmgren-Miner cumulative damage rule.

$$N = \frac{D_{cr}A}{k_f^m \Delta\sigma} \tag{1}$$

In this model, it is assumed that A, D_{CR}, and k_f all follow a lognormal distribution with $\Delta\sigma$ and m constant. The lognormal distribution has the following probability density function, and has previously been shown to be a reasonable fit for ship-like structure fatigue data (Collette and Incecik 2006):

$$p(x) = \frac{1}{\zeta\sqrt{2\pi}x}\exp\left(-\frac{\left(\ln(x)-\lambda\right)^2}{2\zeta^2}\right) \tag{2}$$

Under these assumptions, it can be shown that N also follows a lognormal distribution, with the following parameters:

$$\lambda_I = \lambda_{Dcr} + \lambda_{Af} - m\left(\lambda_{kf} + \left(\ln\left(\Delta\sigma\right)\right)\right)$$
$$\zeta_I = \sqrt{\zeta_{Dcr}^2 + \zeta_{Af}^2 + \left(m\zeta_{kf}\right)^2} \quad (3)$$

With this distribution, an analytical solution to the crack initiation reliability problem is available without resorting to methods such as FORM. It is significant that both the instantaneous probability and the cumulative probability of a crack occurring at any point in time corresponds to a number of stress cycles and can be readily determined and used in an updating framework.

This model is extended to include an efficient formula for forecasting the expected number of fatigue cracks over time in grillage-type structures with multiple similar fatigue-prone details as is shown below:

$$\mathrm{P(n)} = \frac{d!}{n!(d-n)!}[(1-p)^{d-n}(p^n)] \quad (4)$$

Where *P(n)* is the probability of *n* cracks occurring at an instant in time, *d* is the number of details on the considered grillage, and *p* is the probability of a crack occurring at an instant in time associated with a number of experienced stress cycles from Eq. 2.

Fatigue Capacity Updating Using Hierarchical Bayesian Model

The goal of the Bayesian Network is to develop revised parameter estimates and estimates for future fatigue cracking through an inference approach based on observed failures. Multiple Bayesian Networks were considered and can be seen below. In this approach, the Bayesian network encodes discrete possible values of the log scale parameters, λ, of the lognormal distributions governing failure in Eqs. 1 to 4, as well as discrete values of the working stress range. In this work, the ability to update the shape parameter of the lognormal distribution was not considered. It was found that the updating power of the Bayesian Network with a combined *A* and D_{cr} node had significantly better updating power. This is not surprising given that these variables are directly coupled within Eq. 1, and either could be adjusted to impact the numerator of Eq. 1.

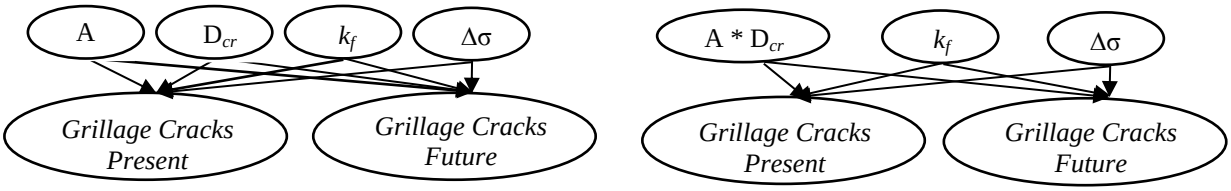

Figure 1. Proposed fatigue updating network

The number of bins for the parent nodes was three, three, and five for $A^* D_{cr}$, k_f, and $\Delta\sigma$, respectively; this represents 45 potential reliability models that could describe the as-built ship. Uniform non-informative priors were assumed for the initial network. By supplying in-service failure statistics to the network in the form of the number of details that have cracked, it is possible to update the underlying variables and refine the future cracking prediction.

Proposed Lifetime Updating Framework

As discussed in the introduction, simply allowing the Bayesian networks in Figure 1 to update the average stress on the vessel will not correctly account for changing operational patterns. Instead, we seek an approach to correct the engineering load prediction model based on observations, and use the corrected model in future predictions. To implement this model, a standard approach is taken where the ship's lifetime exposure at sea can be divided into many blocks or cells (Sikora, Michaelson, and Ayyub 2002). Each cell corresponds to an "operational mode" defined by sea state (*SS*), speed (*U*) and heading angle (β). The size of the cell should be small enough so that a statistically stationary condition can be assumed within each cell. Figure 2 shows the updating approach within this framework. Monitoring data is available for load cell 1 to load cell *n* (denoted yellow); while the load cell *k* does not have any observed data available and the load response need to be predicted (denoted white). An engineering load prediction model, which is normally used during the design stage based on spectral method, has been chosen and is shown inside the first dashed rectangle. This engineering model is expected to be controlled by several parameters $\Theta_i = (\theta_1, \theta_2, \theta_3, \cdots), i = 1, 2, 3, \cdots m$. A direct estimation of response distribution using the design stage engineering model would not necessarily match the

observed loading, owing to imperfect or uncertain estimates of the parameters, Θ. These uncertainties can be mainly described as a mean shift and also as the change of variance and shape of distribution. By integrating the life cycle information of observed load cells, those cell-based parameters Θ are expected to be updated. Ideally, Θ should be independent of load cells parameters to allow prediction for the load cells in unobserved data.

In most of cases, it is difficult to conclude that the difference of Θ between updated value and design value is unbiased. Therefore, a hierarchical Bayesian model is further developed with latent variables. The purpose is to predict Θ_k in the unobserved load cells by training the data from observed load cells. Then the Θ_k can further be used to update the response distribution of unobserved load cells, while the initial design guess can also be taken into account as prior information. This proposed framework is expected to lead to a refined prediction of response in those unobserved cells, which is critical to the lifetime load updating using SHM data.

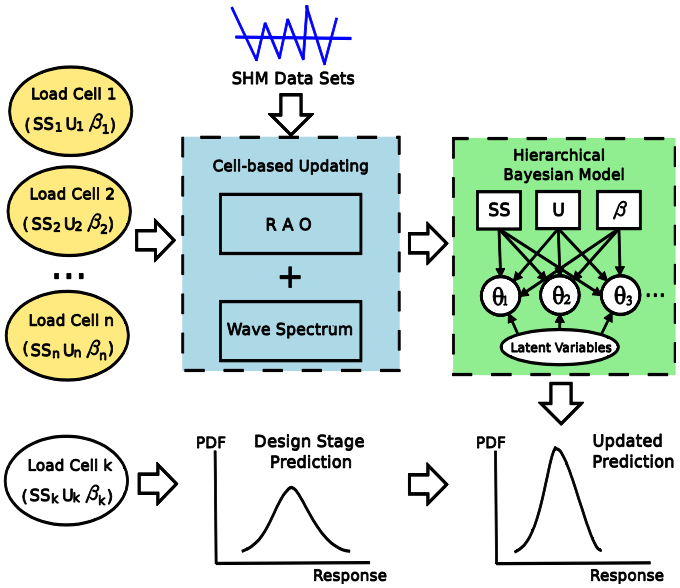

Figure 2. Proposed lifetime load updating framework

Cell-based Updating Strategy

Within the framework proposed, it is necessary to have an engineering prediction tool to estimate the loading, hence the structural stress response provided within each cell. In this work, the cell-based updating is based on Jensen's closed form expression (Pedersen and Jensen 2009) of vertical wave induced bending moment RAO Φ_M, which is one of the dominant sources of fatigue loading on most large vessels. The expression is derived analytically by using linear strip theory from a box shaped vessel and the small contribution of hydrodynamic damping is neglected.

$$\frac{\Phi_M}{\rho g B_0 L^2} = \kappa \frac{1-kT}{(k_e L)^2}\left[1-\cos\left(\frac{k_e L}{2}\right)-\frac{k_e L}{4}\sin\left(\frac{k_e L}{2}\right)\right] F_V(Fn) F_C(C_b) \sqrt[3]{|\cos\beta|} \quad (5)$$

An ITTC recommended modified Pierson-Moskowitz family is used here with an input of significant wave height H_s and average period T_0. The response of wave induced vertical bending moment (VBM) can then be calculated according to equation below.

$$S_{VBM}(\omega) = S_{wave}(\omega) \times \Phi_M^2 \quad (6)$$

For a broad-banded Gaussian process, the cumulative distribution function (CDF) of response peak x is given by Ochi (Ochi 1990).

$$F_p(x) = \Phi\left(\frac{u}{\eta}\right) - \sqrt{1-\eta^2}\exp\left(-\frac{1}{2}u^2\right)\left(1-\Phi\left(-\frac{\sqrt{1-\eta^2}}{\eta}u\right)\right) \quad (7)$$

where $u = x/\sqrt{m_0}$ is the normalized response with mean of zero and standard deviation of one. η is the bandwidth defined by Eq. 4, where m_i is the ith spectral moment.

$$\eta = \sqrt{1-m_2^2/m_0 m_4} \quad (8)$$

The non-Gaussian characteristics of the response will be considered since such nonlinearities are common for vessel structures subject to wave loads. Various non-Gaussian models have been formulated through series transformation, and these models use non-Gaussian statistical moments (skewness and kurtosis) to form a non-Gaussian contribution of a Gaussian process, often by using Hermite series (Winterstein 1988; Winterstein and Kashef 2000). In this paper, non-Gaussian behavior for the vertical bending sagging moment will be studied

here by only considering skewness μ_3, since kurtosis has a smaller impact on increasing the moment. For a slightly non-Gaussian narrow banded process ($\varepsilon = 0$), u is a function of μ_3. However, for a non-narrow banded distribution, a certain amount of error will be involved if ε is still calculated from the spectral moments with non-Gaussian skewness. A correction factor of χ has been introduced which can written as:

$$\eta' = \chi\eta \tag{9}$$

According to this framework, three uncertainty parameters $\Theta = (k, \mu_3, \chi)$ are specified to represent the difference between engineering model and real time measurement.

(1) A scaling factor of k for the speed correction factor $F_V(Fn)$ in Eq. 5. This represents an over or under estimation of the response RAO model. This factor will only change the magnitude of response peak by changing the response spectra. However, the peak distribution shape will be not changed.

(2) A skewness factor μ_3. This represents the non-Gaussian behavior of the response which is assumed mainly comes from skewness. As skewness is a measure of symmetry, thus for Gaussian process, $\mu_3$will equal to zero. Change of skewness for sagging moment will change the shape of peak distribution, especially the probability of observing a large peak.

(3) A bandwidth correction factor χ. This is an adjustment of bandwidth calculated from Gaussian process. Notice that the updated bandwidth ε' only represents a variable that can be applied into a Gaussian process peak distribution, thus doesn't have very strong physical meaning. However, for an engineering model, this can facilitate a quick approximation of response peak distribution by applying the knowledge of Gaussian process for design purpose.

According to the model above, a design stage prediction model for response load can be expressed in Eq. 10 with a prediction error term ε.

$$F_p(x) = g(x|k, \mu_3, \chi) + \varepsilon \tag{10}$$

It is assumed here that initial prior distribution of parameters is $f_0\ (k, \mu_3\ , \chi)$ and εsatisfies a normal distribution with mean 0 and standard deviation of σ_ε. With collected SHM data for corresponding load cell, the posterior distribution of $f\ (k, \mu_3\ , \chi|D)$ can be obtained via a standard Markov Chain Monte Carlo (MCMC) inference (Gamerman and Lopes 2006). Although it is time consuming and may have some trouble converging in all cases, one big advantage of MCMC is that it can tolerate a highly nonlinear model with all continuously distributed parameters. The predictive distribution of response can be further computed via the integral through each parameter.

$$F_p(x|D) = \int_{\Theta=(k,\mu_3,\chi)} f(k, \mu_3, \chi|D) g(x|k, \mu_3, \chi) d\theta \tag{11}$$

Lifetime Wave Load Updating Using Hierarchical Bayesian Model

The goal of lifetime load updating is to predict the error in the loading estimate for unobserved load cells by learning information about the error in the observed cells. According to Eq. 10, the VBM distribution in each cell is determined by three parameters: k, μ_3 and χ. Therefore, if the parameters in unobserved cells can be obtained, then VBM distribution can also be predicted. A hierarchical Bayesian model is built as shown in Figure 2 to link the distributions of parameters between observed and unobserved cells. Two types of cases have been considered separately: when the empirical knowledge can provide estimations of parameters (such as μ_3 and k) or when the empirical knowledge cannot provide estimations (such as χ).

For case one, assume there is an explicit equation h available for an estimation of parameters, then the corresponding Bayesian model can be written as

$$\Theta_i = h(L, U_i, \cos\beta_i\ , SS_i) + \varepsilon \tag{12}$$

where $L = (l_1\ , l_2\ , l_3\ , \cdots)$ and ε are the latent variables which are assumed unchanged among different cells and is the error term to measure the bias between empirical prediction and observed evidence. For the case two, since there is no empirical knowledge, a simple linear response surface can be built similarly, as shown in Eq. 13.

$$\Theta_i = l_1 + l_2 U_i + l_3 \cos\beta_i + l_4 SS_i + \varepsilon \tag{13}$$

The posterior of distributions of latent variables are then inferred by using MCMC algorithm again. This allows for the computation of updating loading in unobserved cells.

RESULTS AND DISCUSSIONS

Updating Fatigue Strength Bayesian Network Alone

Initially, the Bayesian network in Figure 1 was used alone to predict and update the future fatigue crack state. Forward inference was used to determine $P(n_{present})$ and $P(n_{future})$ without pre-existing evidence and used uniform non-informative priors for the root nodes in the network. This represents an average cracking history

over the 45 potential reliability models encoded in the network. Separately, a Monte Carlo algorithm was initialized with a single reliability model selected from the 45 possible reliability models contained in the network. Using a sample size of five ships, a realization of cracking history was developed for this reliability model. This was treated as the "actual" situation on the vessel, and used to judge how well the Bayesian network could identify this "actual" situation based on the evidence compared to the 44 other incorrect reliability models. The results of the Monte Carlo simulation were presented approximately half way through service life to the Bayesian network as evidence on the cracking nodes. Junction-tree inference was used to compute $P(\Delta\sigma|n_{present})$, $P(A * D_{cr}|n_{present})$ and $P(k_f|n_{present})$. These revised posterior probabilities of the 45 possible reliability models were then used with forward inference to compute $P(n_{present})$ and $P(n_{future})$ (without evidence). These predictions were then compared to the Monte Carlo results. If the network was able to update successfully based on the evidence, the revised prediction for the present and future would fall closer to the Monte Carlo results than the initial estimate, which was averaged over all 45 potential reliability models. This test was repeated for several grillages and levels of observed cracking, as shown in Table 1.

Table 1. Results of updating based on single crack inspection at $4{\cdot}10^6$ cycles

			Number of Cracks (% error)		
Mean Number of Simulated Cracks	Point in Time/ Number of Stress Cycles	Distribution	Mean	Median	Std Dev
21/100	Present: $4(10^6)$	Actual	23	22	4
		BN Initial Est.	11 (52%)	5 (77%)	13 (225%)
		BN Updated Est.	23 (0%)	22 (0%)	14 (250%)
	Future: $1(10^7)$	Actual	54	56	5
		BN Initial Est.	31 (45%)	29 (48%)	24 (380%)
		BN Updated Est.	54 (4%)	58 (4%)	19 (280%)
9/100	Present: $4(10^6)$	Actual	11	20	3
		BN Initial Est.	11 (0%)	5 (75%)	13 (333%)
		BN Updated Est.	13 (18%)	9 (55%)	13 (333%)
	Future: $1(10^7)$	Actual	41	40	5
		BN Initial Est.	31 (24%)	29 (28%)	24 (380%)
		BN Updated Est.	38 (7%)	38 (5%)	22 (340%)
16/150	Present: $4(10^6)$	Actual	17	16	4
		BN Initial Est.	15 (12%)	7 (56%)	19 (375%)
		BN Updated Est.	22 (29%)	18 (13%)	23 (475%)
	Future: $1(10^7)$	Actual	61	60	6
		BN Initial Est.	46 (25%)	44 (27%)	36 (500%)
		BN Updated Est.	62 (2%)	66 (10%)	33 (450%)
Average Percent Error Decrease From Updating			**14%**	**34%**	**8%**

It can be seen from Table 1 that for 21/100 simulated cracks, the means and medians for the updated present and future values are within 5% of the analytical values. For 9/100 and 16/150 simulated cracks (approximately 10% of details cracked), the mean and median errors after updating are within 10% of the future prediction but reach 55% error for the present point in time. This greater error rate can be attributed to the reduced information from which the Bayesian network is updating. In these cases, it is around 10% while the first case had over 20% of its details cracked. Standard deviation error is much more significant ranging from 250%-475%. This demonstrates that the Bayesian network updating is struggling to accurately produce the appropriate shape for the probability distribution. This is not surprising given that the shape parameter ζ, of the lognormal distribution was not under control of the network. Despite the comparatively large error shown in standard deviation, the Bayesian network updating is able to decrease the standard deviation error an average of 8% from the initial estimate. More significantly, mean and median are reduced 14% and 34%, respectively.

Updating Lifetime Wave Loading Alone

To evaluate the proposed updating framework, the joint high-speed sealift (JHSS) vessel (Frangopol et al. 2012) is studied with load cells being divided into several intervals. The probability of occurrence is assumed first for each load cell. A time domain VBM data is then simulated according to Jensen's method with a skewness factor assumed by Eq. 14 and scaling factor assumed by Eq. 15.

$$\mu_3 \cong aH_s \cdot \left(1 - \exp\left(\frac{-bFn}{|cos\beta|}\right)\right) \tag{14}$$

$$k = 1 \tag{15}$$

The peak points have been selected to plot a CDF of VBM. A cell-based updating strategy is performed first for all the load cells to find the posterior distributions of k, χ, and μ_3. Then, given the number of observed load cells, a hierarchical Bayesian network is further built with observed load cells sampled from their probability of occurrence. Two models are compared: an empirical equation (EE) based model according to Eq. 12 with latent variables a, b and ε for skewness and latent variable ϵ for scaling factor, and a linear response (LR) surface model according to Eq. 13 built under different probability levels. A critical factor in the success of a method is to be able to find the correct distributions given a limited amount of observation data. The error in these distributions is summed under different probability levels. Then, the mean and standard deviation of errors among all load cells prediction are shown in Figure 3.

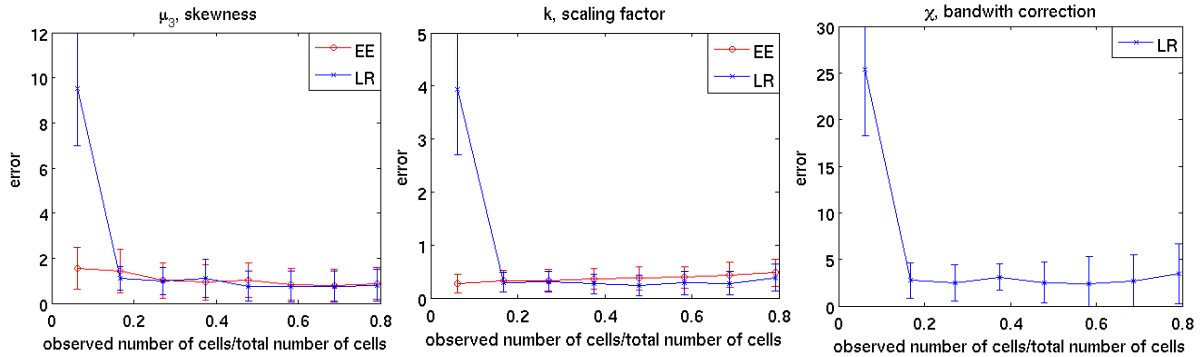

Figure 3. The error of predicting load cell parameters with increased observed load cells

Figure 3 demonstrates that when the empirical equation is given (μ_3 and k), the error of EE-based method is much less than the LR-based method when less than 20% load cells are observed. However, when the empirical equation is not available (χ), only the LR-based method can be applied. The prior and posterior distributions for the latent variables of μ_3 and k are shown in Figure 4 and Figure 5, respectively, when almost 80% of load cells are observed. Since the time domain data is generated according to those assumed latent variables, the MCMC method is able to search the optimum posterior distribution of variables and narrow the distribution into a much smaller range.

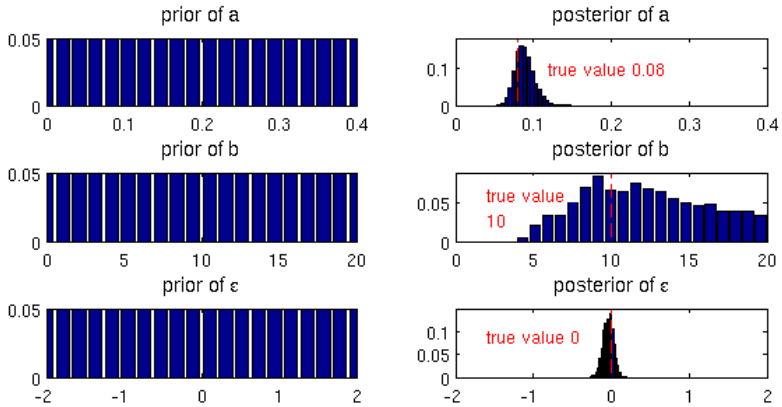

Figure 4. The comparisons of prior and posterior distributions of latent variables for μ_3

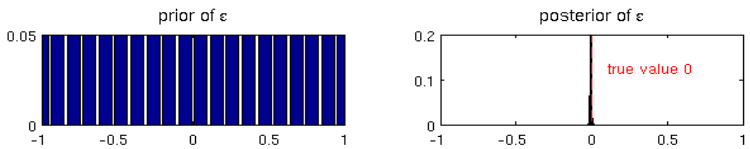

Figure 5. The comparisons of prior and posterior distributions of latent variables for k

With those posterior distributions of latent variables available, the CDF of VBM can be further updated. When a highly non-Gaussian and broad-banded response is presented, the updated distribution is generally more accurate than Jensen's method in predicting the VBM response. An example of VBM prediction in an unobserved load cell is shown in Figure 6 (left). The ship's lifetime load can further be updated, as shown in Figure 6 (right). Since the probability of occurrence of those high skewness or bandwidth load cells are

generally low and the original data is also generated according to Jensen's method, less difference can be seen between Jensen' prediction and MCMC updated prediction.

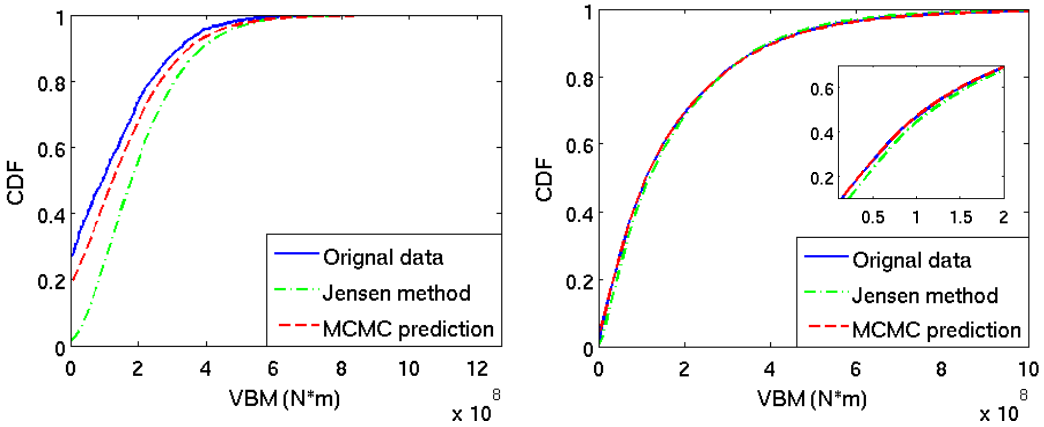

Figure 6. VBM response prediction for a unobserved load cell (sea state 8, heading angle 45°, speed 40 knots, left) and the lifetime load prediction based on 20% observed load cells (right)

Comparison of Future Prediction of Cracking with Both Loading and Strength Updates

A method is required to integrate the updated loading prediction presented the in the previous section with the Bayesian fatigue network. Initially, a simple approach is proposed where the updated load estimate transforms the prior distribution of the stress variable states from a uniform non-informative prior to a prior with a higher probability in the stress bin corresponding to the updated load estimate. Table 2 presents the results for increasing the prior probability of the stress level used in the Monte Carlo simulation ("true prior") to p=0.6, p=0.7, and p=1.0 from the p=0.2 non-informative prior used initially. The remaining four stress levels were assigned lower uniform priors so that the total probability over stress models summed to 1.0. When p=1.0, the stress variable is no longer stochastic in the Bayesian network and all updates will adjust the fatigue capacity terms.

Table 2. Bayesian network updating result with increasingly informative priors based on load updating

			Number of Cracks (% error)		
Mean Number of Simulated Cracks	Point in Time/ Number of Stress Cycles	Distribution	Mean	Median	Std Dev
21/100	Present: 4(106)	Actual	23	22	4
		BN Initial Est.	11 (52%)	5 (77%)	13 (225%)
		BN Updated Est.	23 (0%)	23 (5%)	14 (250%)
		BN Updated Est. p=0.6 Δσ true prior	23 (0%)	23 (5%)	13 (225%)
		BN Updated Est. p=0.7 Δσ true prior	23 (0%)	22 (0%)	13 (225%)
		BN Updated Est. p=1.0 Δσ true prior	23 (0%)	22 (0%)	12 (200%)
	Future: 1(107)	Actual	56	56	5
		BN Initial Est.	31 (45%)	29 (48%)	24 (380%)
		BN Updated Est.	54 (4%)	58 (4%)	19 (280%)
		BN Updated Est. p=0.6 Δσ true prior	54 (4%)	57 (2%)	18 (260%)
		BN Updated Est. p=0.7 Δσ true prior	55 (2%)	56 (0%)	18 (260%)
		BN Updated Est. p=1.0 Δσ true prior	55 (2%)	56 (0%)	16 (220%)

The above table demonstrates the Bayesian network ability to update with greater accuracy given a prior certainty of stress range. It is evident that with greater prior certainty ranging from p=0.6-1.0 the Bayesian network is able to determine the mean, median, and standard deviations with greater accuracy. In both the present and future time in Table 2, the mean and median predictions are within 5% for true priors of p=0.6, and

2% for true priors p=0.7 and 1.0. More cases were run than presented in Table 2, and while the trend of reducing error with more informative priors held, it is interesting to note that there was some oscillation in the reduction. Clearly, a robust method of adjusting the prior based on the confidence in the loading estimate is still needed. Standard deviation predictions are more accurate as well, but without nodes for shape parameters, it will continue to be difficult to accurately determine the appropriate values. Future addition of the lognormal shape parameters, ζ, should help alleviate this updating issue.

CONCLUSIONS

A new approach to updating structural performance models of marine structures has been presented. A key feature of the model is that two updating approaches are used: structural capacity is updated via a Bayesian network that integrates measurements with future predictions. Owing to the non-stationary aspects of vessel loading, an intrusive updating approach is proposed for loading where correcting factors to the underlying loading model are determined based upon observations, and then the corrected loading model is used to forecast future loading in unobserved conditions. The proposed approaches were demonstrated independently, showing reasonable performance assuming sufficient in-service observations are available. A combined approach, where the updated loading is incorporated as an informative prior to the Bayesian network was also presented, which further increased the performance of the updating approach.

ACKNOWLEDGMENTS

The authors would like to thank Dr. Paul Hess, ONR Code 331 who supported this work under grant N00014-11-1-0135.

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