Bayesian Networks for Model Updating Inspection Support of Marine Structures Subject to Fatigue

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ABSTRACT: There is significant uncertainty in the structural health and resulting capabilities of a marine structure during service life. Design-stage marine structural engineering models offer limited information on the as-built structure's health during its service life. Despite copious amounts of data provided by structural monitoring techniques, synthesizing these different data types to offer support in decision making for inspection remains challenging and underexplored. A Bayesian network data to decision framework fusing through-life inspection data with design-stage fatigue calculations is demonstrated to afford data fusion and inspection extent decision support. Using parametric encoding for a Weibull pressure distribution governing cyclic loading, and a lognormal probabilistic fatigue initiation model, the network represents a large stiffened metallic grillage with fatigue-critical details typical of a marine structure. Updating is performed with inspection observation and maximum strain values. Extension of the Bayesian network to an Influence Diagram with utility and decision nodes offers inspection extent decision support. The ability of the network approach to provide reasonable inspection guidance and forecast of future structural performance is tracked for different evidence sets. Recommendations for adapting the network approach for fatigue life support are drawn based on the systematic study conducted.

An increased awareness of a vessel's structural condition through its service life could significantly increase the safety and operational capability of the vessel. Such awareness would also grant the ability to make cost reducing inspection and maintenance decisions. Over the past several decades our ability to sense and record structural performance data has increased dramatically through new sensor and data acquisition systems (Wang, Lynch, and Sohn 2014). Monitoring techniques include a variety of sensors recording related but different data types at high sampling rates, often on the order of hundreds of hertz. As a result, as Collette and Lynch describe, "we swim in an ocean of data but remain thirsty for information" (Collette and Lynch 2013). In addition to data recorded by sensing methods, there are many phenomena physically recorded in the structure that can be used for model updating. The abovementioned benefits of structural awareness can only be achieved with a data-to-decision (D2D) framework. D2D requires both the interpretation of abundant data to yield relevant information, and a decision support system capable of evaluating the information produced. Data acquired from these systems can be used to update structural forecasting models to make better life cycle structural updating decisions. The current work examines techniques to interpret and synthesize the physical record, which has seen limited investigation, and update design-stage engineering models to more closely match the current condition of the vessel. These updated models can then be used for inspection decision support. A Bayesian network extended to an Influence Diagram framework is used to fuse different in-service observations with a common underlying structural model. This approach is explored for a stiffened grillage subject to fatigue failures and permanent set of the grillage plate.

Application of Bayesian networks in the realm of Risk Based Inspection for fatigue damages has been studied by Goyet et al. (2011) who introduced a Probabilistic System Approach including economical optimization of the FPSO service life based on a hierarchical model of the hull. This approach uses Bayesian networks to propagate probabilities from component level to the system level. Heredia-Zavoni, Silva-González, and Montes-Iturrizaga (2008) presented a general framework for integrity management of offshore steel structures allowing for the risk based planning of inspection and maintenance activities accounting for both deterioration and damage processes using a Bayesian network for decision making. The proposed risk based inspection (RBI) framework combines damage processes and uses a threshold acceptable total system failure probability to dictate optimal inspection points. Sørensen (2011) explored the use of Bayesian pre-posterior decision theory to evaluate deterioration from various sources being monitored and inspected. Further supporting the use of Bayesian networks in application to RBIs of vessel structural health, Tammer and Kaminski (2013) reviewed the use of this methodology for determining the inspection scope, and inspection intervals of FPSOs in application to fatigue related degradation, determining it to have an inevitable role in future decision making. These publications show there has been application of Bayesian statistics for evaluation of structural health and inspection periodicity. However, the use of Bayesian networks and Influence Diagrams for synthesis of multiple data types for structural health model updating and decision making has not been explored. Leveraging fusion of multiple stochastic data types and sources is presently being overlooked.

The present work focuses on the problem of updating probabilistic structural fatigue crack initiation models for inspection extent decision support of marine structures. Marine structures are inherently susceptible to fatigue failures as the primary stress field alternates between tension and compression under wave loading. Without repair, these cracks grow and can cause fracture potentially resulting in catastrophic failure.

Synthesizing data from permanent set (deformation of shell plates from local sea pressure exceeding elastic limit), crack initiation, and a maximum strain recording, the presented method demonstrates the ability to provide both model updating of the in-service vessel and decision support for inspection extents. Updating capabilities are demonstrated via Monte Carlo simulation. Results are shown for evidence fused from three distinct types of observations providing inspection extent strategies for the present and a future point in time.

1. METHODOLOGY

Ships are typically built in small-run production settings. Economically, this makes prototype structural testing cost-prohibitive. Thus, a common challenge is how to interpret in-service inspections in light of a non-validated structural design model. Here, a series of design-stage structural prediction models related to observable outcomes are integrated into a Bayesian network. The underlying parameters of these models are assumed to be stochastic. Through service-life updating, the posterior belief in these parameters is adjusted to better reflect the as-built vessel.

The overall methodology used includes a parametrically encoded Bayesian network extended to an Influence Diagram for decision support. The network is encoded with reliability models from design priors and is updated with evidence from fatigue failures, permanent set, and the maximum recorded strain of a grillage structure undergoing lateral (normal) pressure loading. Posterior distributions more accurately represent the in-service structural reliability model and are then used to find the maximum expected utility for decision of inspection extent for the considered juncture and a future point. The future inspection strategy is determined assuming execution of the present inspection strategy with the highest utility.

1.1. Fatigue Model

Sections 1.1-1.3 are taken from Groden and Collette (2013); it did not appear in printed proceedings so it is reproduced here. The fatigue capacity model used was presented previously by (Collette 2011). It uses a lognormal modeling approach to solve the S-N crack initiation reliability problem analytically, inspired by Wirsching (1984). In this approach, the number of cycles to fatigue crack initiation at a given structural location is determined to by the 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 modeling uncertainty factor, and D_{cr} is the cumulative damage index from the Palmgren-Miner cumulative damage rule.

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

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):

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

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

This model is extended via 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:

$$\mathrm{P(n)} = \frac{d!}{n!(d-n)!}[(1-p)^{d-n}(p^n)] \tag{3}$$

Where P(n) is the probability of n cracks occurring at an instant in time, d is the number of total fatigue-prone details on the considered grillage that could crack, 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.

1.2. Permanent Set Model

Like fatigue cracking, permanent deformations, or set, of the plating on a ship is a detectible structural failure mode amenable to updating approaches. Hughes' semi-empirical method (Hughes, Paik, and Béghin 2010) was used to model permanent set. Hughes developed this method to provide designers with a rapid calculation for the approximate load required for a plate to experience a specified amount of permanent set. The basis for this method is the following formula which relates a uniformly distributed pressure load parameter Q, permanent deflection of the plate w_p, the plate characteristics including its length, width and their ratio, b, a, and β respectively, material characteristics, and the uniform pressure.

$$\mathrm{Q} = Q_Y + T(R_w)(\Delta Q_0\left(\beta, \frac{a}{b}\right) + \Delta Q_1\left(\beta, \frac{a}{b}\right) R_w \tag{4}$$

where

$$Q_Y = \frac{2}{\sqrt{(1-v+v^2)\beta^4}}\left(1 + 1.46\left(\frac{b}{a}\right)^{1.87}\right),$$

$$-\Delta Q_0 = \frac{1 + 3.24\beta^{0.0687}\left(\frac{b}{a}\right)^{1.389}}{\sqrt{(1-v+v^2)\beta^4}},$$

$$-\Delta Q_1 = 1.92\frac{\left(\frac{b}{a}\right)^{1.86}}{\beta^{0.94}},$$

$$R_w = \frac{w_p}{w_{p0}},$$

$$\frac{w_{p0}}{t} = \frac{\beta^2}{48\sqrt{(1-v+v^2)}},$$

$$T(R_w) = \left\{ \begin{array}{cc} ((1-(1-R_w)^3)^{\frac{1}{3}} & R_w \leq 1 \\ 1 & R_w > 1 \end{array} \right\}.$$

R_w is nondimensional permanent set, ν is Poisson's ratio, and Q_Y is the initial yielding load for which permanent set commences. The load parameter, Q has two regimes, the first defined by Q_Y which is non-linear, and the second being linearly proportional defined by ΔQ_0 and ΔQ_1, producing a "hockey-stick" relationship as can be seen in Figure 1. Permanent set observation provides the network with data pertaining to the maximum experienced stress, however, should set go without observation owing to low experienced extreme pressure, strain sensors and measurement devices can still be used.

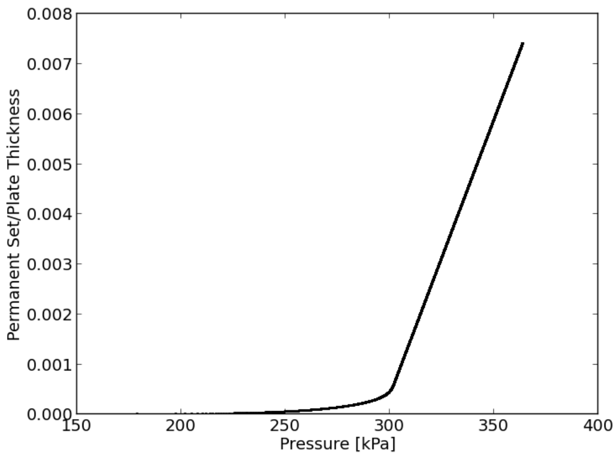

Figure 1: Permanent set versus pressure.

1.3. Probabilistic Loading Model

The Bayesian network parametrically encodes a probabilistic pressure distribution for application to the permanent set and fatigue models. The stress to be considered in the fatigue model is directly proportional to the pressure described by a two-parameter Weibull distribution, with independence assumed between successive pressure peaks. The PDF and CDF of the Weibull distribution are given by:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} \exp\left(-\left(\frac{x}{\alpha}\right)^{\beta}\right) \qquad (5)$$

$$F(x) = 1 - \exp\left(-\left(\frac{x}{\alpha}\right)^{\beta}\right) \qquad (6)$$

An equivalent constant amplitude stress range can be determined by taking expected moments of the Weibull distribution and used with the fatigue model presented previously. While the Weibull distribution will govern the fatigue damage process, permanent set is governed instead by the extreme pressure during the operational period up until the point of inspection. If the individual loads follow a Weibull distribution, the highest load out of n repeated samples will approach a Gumble extreme value distribution as n grows. The PDF and CDF of the Gumbel distribution are given by:

$$f(x) = \frac{1}{\sigma}\exp\left(-\frac{x-x_n}{\sigma} - \exp\left(-\frac{x-x_n}{\sigma}\right)\right) \qquad (7)$$

$$F(x) = \exp\left(-\exp\left(-\frac{x-x_n}{\sigma}\right)\right) \qquad (8)$$

Soares and Teixeira (2000) proposed an approximate formulation to determine the parameters of the extreme value Gumbel distribution from the underlying Weibull distribution given a number of cycles, n:

$$x_n = \alpha(\ln(n))^{\frac{1}{\beta}} \qquad (9)$$

$$\sigma = \frac{\alpha}{\beta}(\ln(n))^{\frac{1}{\beta}-1} \qquad (10)$$

1.4. Bayesian Networks

The goal of the Bayesian network is to synthesize data from inspection observations to develop a better understanding of the underlying reliability model. In this approach the Bayesian network encodes discrete possible values of the log scale and shape parameters of the lognormal distributions governing fatigue failure in Eqs. 1 through 3 and the Weibull pressure distribution's parameters from Eqs. 5 and 6. This is known as parametric encoding as opposed to a conventional, direct encoding where the discrete probability bins are established within the nodes according to their respective distributions. Parametric encoding requires far fewer observations than non-parametric methods in order to accurately estimate the underlying distribution (James et al. 2013). It was found that the updating power of the Bayesian network with a combined A and D_{cr} node had significantly better updating power than treating these nodes separately as Bayesian updating cannot realistically distribute error between them owing to the form of Eq. 1 .

1.5. Influence Diagrams

Through the addition of utility functions and decision nodes, it is possible to use Bayesian networks as a decision support tool. Networks augmented with the utility and decision nodes are known as influence diagrams and are compact representations of a joint expected utility function. The solution to a decision problem is a matter of determining the strategy that will provide the highest utility value to the decision maker. Therefore, construction of a utility function accurately representing the value of the potential strategies is critical to the effectiveness of the influence diagram's ability to provide decision support. Similar to a Bayesian network Influence Diagrams rely on the chain rule for finding the expected utility for each action, a, in determination of $P(h_j|\varepsilon)$, with ε as evidence, and h hypothesis.

$$\mathrm{EU}(a_i) = \sum_j U(a_i,\ h_j) P(h_j|\varepsilon) \tag{11}$$

Utility functions provide a utility value for each combination of related node states. After performing inference with the provided evidence, the maximum expected utility value is determined and the corresponding strategy states are selected and presented as the optimal decision given the evidence provided.

Figure 2 depicts the completed network. Three bins were designated for each of the root nodes, scale and shape $A^* D_{cr}$, mean k_f, and the pressure distribution's Weibull scale and shape parameters. A node with nine bins for the maximum strain reading was added influencing the pressure nodes and ultimately the stress range. The grillage node was given 100 statistically identical fatigue-prone details. Each detail follows the lognormal life distribution given previously. The network as constructed represents 729 potential reliability models that could describe the as-built vessel. All parent nodes have an initial uniform probability distribution which means that the network initially assumed equal likelihood of each reliability model being represented.

Figure 2: Proposed inspection decision support Influence Diagram.

2. RESULTS

2.1. Test Case

To serve as a proof of concept test case, a simple yet applicable structural component was needed. The structure considered for use within the models presented herein is a typical stiffened panel from a 5415 hull midship section (Ashe 2009), Figure 3. The particular grillage was chosen for consideration because of its location on the midship section is on the waterline, the area most likely to provide visually observable permanent set from wave impact loads.

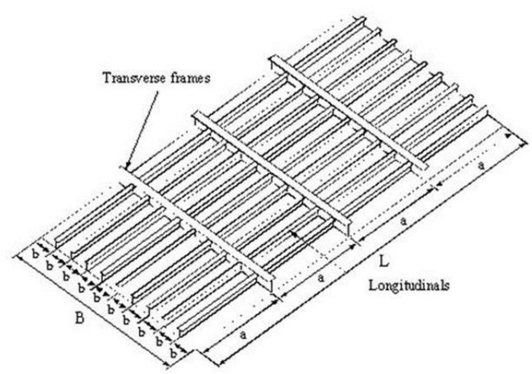

Figure 3: Typical stiffened panel (Paik and Thayamballi 2003).

2.2. Bayesian Updating

The Bayesian network component in Figure 2 was used alone to predict and update the future fatigue crack state. In order to assess the updating capabilities of the network, a Monte Carlo simulation was initialized for five ships with similar fatigue-prone grillages. The Monte Carlo simulation results of cracking histories were provided to the network as synthetic evidence for updating. By comparing the updated distribution's fit to the synthetic data from the initial uniform distribution which is an average of the 729 represented reliability models, the updating strength can be evaluated.

The results of applying fatigue crack initiation, permanent set, and maximum strain measurement are presented in Table 1. Synthetic data from the Monte Carlo simulation which the posterior distributions are trying to match is presented in the first column, followed by the design prior from the uniform distribution. The final row shows the updated results after the fatigue cracking, permanent set, and maximum strain measurements histories are incorporated as evidence, which should fall closer to the first row than the second if the updating is successful. Evidence for the present case is maximum strain recorded and permanent set. For the future case the number of inspected details which have been found to have initiated cracks is provided as evidence in addition to the maximum strain and permanent set histories. This evidence combination was chosen as the network is ultimately providing inspection extent strategies for fatigue crack initiation.

It can be seen that the updating power of the network is significant, reducing error from design prior estimates in all cases except the standard deviation of the present point in time. Interestingly, the median number of initiated cracks forecasted is updated to 0% error while the present median is updated to 16% error; both demonstrate strong updating power and the effectiveness of data synthesis. Given the future case having the additional evidence of the initiated cracks discovered from the first inspection, we expect this increase in updating power. Updating power for standard deviation was poorer. This may be a result of parametric encoding as the design prior has a much larger standard deviation than the synthetic data. This aspect requires further investigation.

Table 1: Bayesian network updating

Case	*Time of Inspection, # of cracks (% error)*			
	Present ($4*10^6$ cycles)		*Future ($1*10^7$ cycles)*	
	Median	*Std Dev*	*Median*	*Std Dev*
Synthetic Data	*44*	*5*	*64*	*5*
Design Prior	*13 (71%)*	*20 (300%)*	*42 (35%)*	*28 (461%)*
Updated	*37 (16%)*	*20 (300%)*	***64 (0%)***	*18 (260%)*

2.3. Inspection Decision Support

The objective of the Influence Diagram is to determine the optimal number of details to inspect for fatigue crack initiation in the present and future inspection points. The present and future nodes are characterized by the number of stress cycles experienced. This affords the ID the ability to provide decision support for an inspection at any point in the vessel's life cycle.

The utility function was developed and constructed to account for the cost associated with each inspected detail, the cost of an initiated crack, and cost of failing to inspect a detail which was in fact cracked. Equation 12 outlines the structure of the utility function.

$$\mathrm{U}(\delta,\gamma,\tau) = \mathrm{p}(\delta,\gamma,\tau,\mathrm{x}) * \left\{\frac{\delta-\gamma}{\delta}\right\}^{\alpha} * \left\{\frac{\delta-\tau}{\delta}\right\}^{\beta} \quad (12)$$

Where δ is the number of total details on the grillage, γ is the number of expected cracks, τ is the number of inspections, and α and β are weighting parameters. The first factor, p, represents the hypergeometric distribution whose probability density function is below in Eq. 13. The second and third factors account for the cost of cracking and detail inspection respectively.

$$\mathrm{p}(\delta,\gamma,\tau,\mathrm{x}) = \frac{\binom{\gamma}{x}\binom{\delta-\gamma}{\tau-x}}{\binom{\delta}{\tau}} \quad (13)$$

A hypergeometric distribution is a no replacement extension of the geometric distribution. This distribution is augmented with an additional bias to increase the likelihood of inspection success 30% from a purely random search. This allows for modeling the inspector's intuition and inspection standard operating procedure.

The decision nodes encode inspection extent strategies for ranges of detail sets. It is assumed that details that have been inspected in the present inspection will either be repaired or do not require inspection in the next successive inspection. Thus, the utility function for the future grillage crack initiation node accounts for the new, undiscovered, initiated cracks forecasted during the covered time step and its inspection ranges are scaled accordingly.

The same Monte Carlo simulated data set was provided to the network for testing as in section 2.2. Table 2 provides the resulting expected utilities for ranges of detail inspection. Since the cost of inspection, which is weighted by β, is the only utility function term which has penalization for greater inspection extent, for reasonable results β needs a value greater than α. In this case weighting parameter α was set to one and β to four. For the first inspection the highest expected utility was observed in the range of 20-30 inspected details and for the second inspection 59-67 inspected details. This means that based on the evidence provided and the updated understanding of the underlying reliability models, the network suggests greatest expected value for 20-30 and 59-67 inspected details respectively. If the suggested inspection strategy is adopted, on average for the five ships, 25 cracks go undiscovered during the first inspection and all cracks are finally discovered during the second inspection. For comparison, conventional inspection was considered inspection of all details during the first inspection and for the second inspection, details on which initiated cracks were not discovered during the first inspection. Thus, from approximately 53% of the conventional inspection extent all of the details which have initiated cracks have been discovered.

Table 2: Normalized utility values for inspection extent decision strategies, α = 1, β =4, 53% conventional inspection extent

Inspection 1		Inspection 2	
# details	Utility	# details	Utility
0-10	0.08	0-8	0.00
10-20	0.20	8-17	0.02
20-30	**0.22**	17-25	0.04
30-40	0.20	25-34	0.06
40-50	0.14	34-42	0.09
50-60	0.09	42-51	0.11
60-70	0.05	51-59	0.14
70-80	0.02	**59-68**	**0.20**
80-90	0.00	68-76	0.17
90-100	0.00	76-85	0.16

Reducing the value of β to two, we can see that the decision strategy changes, Table 3, demonstrating the sensitivity to the utility function composition.

Table 3: Normalized utility values for inspection extent decision strategies, α = 1, β =2, 62% conventional inspection extent

Inspection 1		Inspection 2	
# details	Utility	# details	Utility
0-10	0.03	0-7	0.00
10-20	0.09	7-15	0.00
20-30	0.13	15-22	0.01
30-40	0.15	22-29	0.02
40-50	**0.16**	29-37	0.03
50-60	0.15	37-44	0.05
60-70	0.13	44-51	0.10
70-80	0.09	51-58	0.14
80-90	0.05	58-66	0.23
90-100	0.01	**66-73**	**0.43**

Here, again, after the second inspection, all cracks are discovered but with approximately 62% of a conventional inspection completed. Since β is placed on the only parameter within the utility function reducing the utility value for greater inspection extent, it is logical that for reduced β, the inspection strategy with highest expected utility is for greater inspection extent.

Therefore, the tuning of the utility function and its composition are critical to the strategy suggestion and further investigation of parameter sensitivity is necessary.

3. CONCLUSIONS

A new approach to inspection extent decision support for marine structures has been presented. A framework for an inspection decision support BN augmented to become an ID is described above. Updating was performed from visual observation of cracks, permanent set, and maximum recorded strain. The ability for the parametrically encoded BN fatigue crack initiation model to be adapted to provide decision support in the form of the number of inspected locations has been demonstrated. Future work can modify the model to provide additional strategy suggestion in the form of inspection timing and investigate sensitivity of the utility function weighting parameters. Additionally, investigation of updating techniques to reduce standard deviation error can also be completed.

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