Life-Cycle Maintenance, Monitoring, and Inspection Optimization for Ship Structures under Uncertainty

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ABSTRACT: This paper presents a probabilistic optimization approach for scheduling inspections, monitoring, and maintenance actions along the life-cycle of ships under fatigue deterioration. The optimization approach yields the optimum interventions times and types that facilitate the minimization of expected life-cycle maintenance and inspection cost, maximization of expected service life, and minimization of expected failure cost. Uncertainties associated with the performance prediction, service life estimation with and without maintenance, and the relationship between the degree of damage and the probability of damage detection are considered in the proposed approach. Computing the life-cycle cost, failure cost, and service life is based on an event tree model which takes into consideration the different outcomes of inspection and monitoring actions. The proposed approach is applied to a ship structure under fatigue deterioration.

1. INTRODUCTION

Ships are under continuous gradual deterioration as a result of being exposed to various mechanical stressors and harsh marine environmental effects. Fatigue and corrosion are the main deteriorating mechanisms for such structures (Guedes Soares and Garbatov 1999a,b; Frangopol and Soliman 2015). Frequent inspections and monitoring actions are required to observe the structural performance while maintenance and repair actions are needed to ensure that the structural performance remains above the safe thresholds throughout the required service life. These actions generally represent a burden to the structural manager as they result in an increase in the total life-cycle operational cost. Therefore, an optimal planning strategy is required to determine the ideal time for applying these actions while keeping the structural performance above the safe threshold (Frangopol 2011). However, with the presence of various uncertainties within the performance prediction models, structural deterioration, and inspection outcomes, among others, the proper life-cycle management under the effects of fatigue and corrosion represents a significant challenge for ship managers.

Monitoring systems with the automated ability to detect fatigue crack growth have emerged as an alternative to traditional non-destructive inspection (NDI) methods. The advantage of these systems is that they offer the capacity to detect the damage with minimal disturbance to the operational schedule of the ship. However, long-term monitoring will increase the life-cycle cost of the structure due to the high expenses associated with the monitoring hardware and the continuous need to transfer, process, and interpret the collected data. Additionally, monitoring techniques may have less damage detection abilities compared to traditional NDI techniques.

Although several approaches for probabilistic inspection and/or maintenance planning for fatigue critical structures have been proposed (e.g., Chung et al. 2006; Kim et al. 2013; Kwon and Frangopol 2012; Soliman et al. 2013), less attention has been directed towards (a) the monitoring scheduling problem, in which the optimal times and durations of monitoring actions are established, and (b) the selection of optimal performance observation methodology (i.e., inspection versus monitoring) which fulfill the management objectives given the different cost and capabilities of each of the available techniques. This paper addresses these two issues by proposing a probabilistic approach for intervention (i.e., inspection, monitoring, and maintenance actions) optimization for ship details under fatigue deterioration. Optimum intervention times and types are determined by solving a multi-objective optimization problem which simultaneously minimizes the life-cycle interventions cost, maximizes the expected service life, and minimizes the expected failure cost over the life-cycle. The proposed approach is applied to a critical detail of a steel ship.

2. FATIGUE DAMAGE: A BRIEF REVIEW

Fatigue is one of the main deteriorating mechanisms of steel and aluminum ships. Fatigue cracking may lead to significant inspection and repair costs for ships (Collette 2005). Additionally, it may lead to catastrophic failures if not correctly managed. For a component subjected to elastic stress fluctuations, fatigue damage may accumulate at regions of stress concentration where the local stress exceeds the yield limit of the material. Stress concentrations can occur at the component due to the presence of initial flaws in the material, welding process, or fabrication. Initiation and propagation of cracks in the plastic localized region occurs due to the cumulative damage acting over a certain number of stress fluctuations. These cracks can eventually cause the fracture of the component. This process can be minimized by using better details, avoiding stress concentrations and decreasing the number of welded attachments, among others (Fisher et at. 1998; Barsom and Rolfe 1999).

In this paper, the approach based on the linear elastic fracture mechanics (LEFM) is used to predict the time-dependent crack growth. In this method, the stresses near the crack tip, which are responsible for the crack propagation, are related to the stress intensity factor K. LEFM can be applied through Paris' equation (Paris and Erdogan 1963) for assessing fatigue behavior of steel details. This equation relates the crack growth rate to the range of the stress intensity factor ΔK as follows

$$\frac{da}{dN} = C \cdot (\Delta K)^m \tag{1}$$

where a is the crack size and N is the number of cycles. C and m are material parameters. The range of the stress intensity factor can be expressed as

$$\Delta K = Y(a) \cdot S \cdot \sqrt{\pi a} \tag{2}$$

where S is the stress range and $Y(a)$ is a correction factor which depends on the crack orientation and shape. This correction factor takes into account the effects of the elliptical crack shape, free surface, finite width (or thickness), and non-uniform stress acting on the crack.

Using Equations (1) and (2), the number of cycles associated with a growth in the crack size from an initial size of a_o to a size of a_t can be calculated as

$$N = \frac{1}{C \cdot S^m} \cdot \int_{a_o}^{a_t} \frac{1}{\left(Y(a) \cdot \sqrt{\pi a}\right)^m} da \tag{3}$$

The number of cycles to failure (i.e., when the crack reaches its critical size a_f at the detail) can be obtained by setting a_t in Equation (3) as the critical crack size a_f. By using Monte Carlo simulation with the proper definition of various random variables, the probability density function (PDF) $f_T(t)$ of the time to failure T (i.e., initial service life) of the detail can be achieved. It should be noted that the term *failure* refers to the event in which the crack reaches its critical size. For a small time interval Δt and a given time t, this PDF provides the probability that the failure will occur between the time t and $(t+\Delta t)$. The simulation can also be used to find the cumulative distribution function (CDF) of the time to failure $F_T(t)$ as

$$F_T(t) = P(T \le t) = \int_0^t f_T(u)\,du \tag{4}$$

Figure 1 conceptually shows the CDF of the time to failure with and without repair.

If a specific service life t^* is required, the probability of failure P_f, defined as the probability that the critical crack size will be reached before t^*, is computed as $P_f = P\left(T \le t^*\right) = F_T\left(t^*\right)$.

3. PROBABILITY OF DAMAGE DETECTION

The probability of damage detection (*PoD*) is used in this paper to assess the capacity of the inspection method to detect cracks. This probability is defined as the probability that an existing crack with a specific size will be detected using a given inspection method (Chung et al. 2006). The lognormal CDF form of the *PoD*, adopted in this paper, is given as (Crawshaw and Chambers 1984)

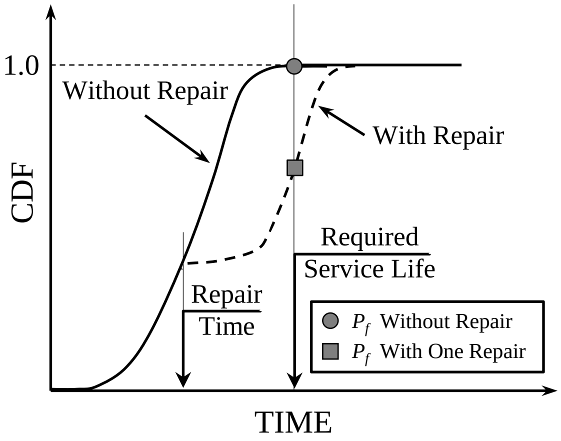

Figure 1 CDF of time to failure (or service life) with and without repair

$$PoD = 1 - \Phi\left[\frac{\ln(a) - \alpha}{\beta}\right] \tag{5}$$

where $\Phi[\cdot]$ denotes the standard normal CDF, a is the crack size, and α and β are the PoD function parameters and they depend on the quality of inspection methods.

The typical procedure when using crack monitoring techniques such as the acoustic emission (AE) method is to perform a follow-up inspection to determine the flaw size by other NDI method (e.g., ultrasonic inspection). However, recent studies shows that it is possible to obtain the probability of damage detection of AE in monitoring the crack growth. Pollock (2007, 2010) shows also that the probability of detecting a certain crack size increases with the increase in the monitoring duration. Hence, in this paper, a time-dependent *PoD* model for monitoring is considered and is expressed as

$$PoD = 1 - \Phi\left[\frac{\ln(a) - \alpha}{\beta}\right] \cdot R_{t_{md}} \tag{6}$$

where $R_{t_{md}}$ is a reduction factor depending on the monitoring duration t_{md}.

4. INTERVENTION OPTIMIZATION

The approach presented in this paper establishes the optimum intervention (i.e., inspection, monitoring, and repair actions) times and types for fatigue critical details. The first step is to predict the time-dependent performance of the structure. Given the various uncertainties associated with this process, performance prediction is performed probabilistically by implementing Monte Carlo simulation. to provide the PDF and CDF of the time to failure. An optimization process is next implemented to find the optimum intervention schedule. The optimum schedules are the ones which simultaneously maximize the service life, minimize the life-cycle intervention cost, and minimizes the expected failure cost. The objectives are evaluated based on the decision tree model presented in Figure 2. As shown in the figure, at a given inspection time, if damage is detected, an in-depth inspection is performed to investigate the degree of damage *d*. If the damage is larger than a certain threshold d_r, repair is performed, otherwise, repair decision is delayed to the next scheduled intervention time.

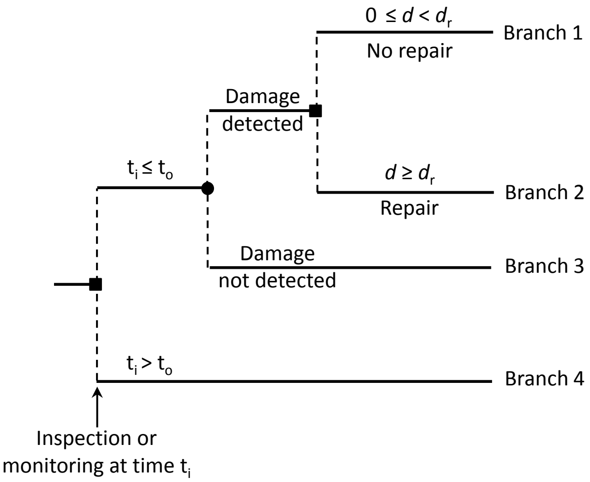

Figure 2 Event tree model for one intervention

4.1. Optimization objectives

Inspection or monitoring actions performed along the service life are crucial to evaluate the structural condition and ensure that the structural performance is above acceptable thresholds. If these actions reveal the presence of structural damage, repair can be applied to reduce the degree of damage (e.g., by replacing the damaged component) resulting in an increase in the structural performance and a corresponding extension in the service life. These repairs also affect the CDF of *T* and reduce the probability of failing before the required service life in the manner shown in Figure 1.

Interventions performed along the service life will increase the life-cycle operational cost. Additionally, the timing of these interventions will also affect the failure probability and the associated expected cost of failure. Thus, it is crucial to obtain a management solution which provides an optimal balance between the expected service life, life-cycle interventions cost, and expected failure cost. In this paper, the effect of repair actions on the service life and the life-cycle interventions cost are quantified through the event tree model shown in Figure 2. Possible outcomes of an inspection or a monitoring action are represented as the branches of the event tree with different occurrence probabilities. For the event tree model in Figure 2, the probabilities of occurrence of the *k*th branch are evaluated as

$$P(B_1) = P(t_i \le t_o) \cdot P(D) \cdot P(NR) \qquad (7a)$$

$$P(B_2) = P(t_i \le t_o) \cdot P(D) \cdot P(R) \qquad (7a)$$

$$P(B_3) = P(t_i \le t_o) \cdot P(ND) \qquad (7a)$$

$$P(B_4) = P(t_i > t_o) \qquad (7a)$$

where $P(B_k)$ is the occurrence probability of the *k*th branch, $P(D)$ and $P(ND)$ are the probabilities of detecting and not detecting the damage, respectively, $P(R)$ and $P(NR)$ are the respective probabilities of performing and not performing a repair action during an intervention, t_i is the intervention time, and t_o is the initial service life without repair.

Next, considering the different branches of the event tree model, the expected service life can be determined as follows

$$E[T] = \sum_{k=1}^{n} P(B_k) \cdot T_k \qquad (8)$$

where $E[T]$ is the expected service life and T_k is the service life associated with the *k*th branch. For Branches 1, 3, and 4, since no repair is performed, the service life will remain the same as the initial service life. For Branch 2, it is assumed that during a repair, the damaged component will be replaced and the initial performance is fully restored.

Similarly, the expected cost including inspection, monitoring and maintenance $E[C^I]$ can be found as

$$E\left[C^I\right] = \sum_{k=1}^{n} P(B_k) \cdot C_k \qquad (9)$$

where C_k is the cost associated with the *k*th branch computed as the summation of the costs of inspection, monitoring, and repair actions performed along the branch.

For a given intervention schedule, the probability that the crack will reach the critical size before reaching the required service life can be found based on the simulation results. This probability is considered herein as the probability of failure and the expected failure cost is obtained as

$$E\left[C^F\right] = P_f \cdot C_f \tag{10}$$

where C_f is the monetary value associated with the failure. The optimization also minimizes this value as one of its objectives.

Using the same procedure, the cost and service life can be found for multiple scheduled inspections and repair actions. Monte Carlo simulation is used in this paper to consider various uncertainties associated with the damage propagation and the estimation of the service life and total cost.

5. ILLUSTRATIVE EXAMPLE

The proposed approach is applied to the ship detail shown in Figure 3. In this study, the joint between bottom plate and longitudinal plate is considered as the critical location subjected to fatigue (Glen et al. 1999). At this location, the fluctuating stress is mainly caused by the hull girder bending. Under longitudinal loading and unloading, the crack in the plate can initiate on the edge connected to the stiffener and propagate away from the stiffener.

To obtain the PDF of the initial service life of the detail, Equation (3) is used with the deterministic parameters and random variables shown in Table 1. In this example, the geometry function $Y(a)$ is assumed to be one (Akpan et al. 2002). The critical crack size is assumed herein to be 50 mm and the required service life is considered 20 years. Monte Carlo simulation with 10^7 samples is next performed to draw samples from the initial service life of the detail. Figure 4 shows the simulation results of the initial service life which is subsequently integrated into the optimization problem to obtain the optimal intervention schedules.

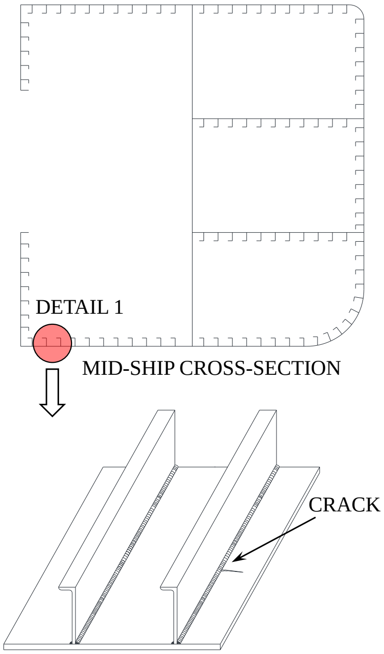

Figure 3 The analyzed detail

5.1. Intervention optimization

In this section, the optimum interventions schedules, including the optimum inspection and/or monitoring times, monitoring durations, and crack size threshold for performing maintenance are obtained. Minimizing the expected life-cycle interventions cost, minimizing expected failure cost, and maximizing the service life are considered as optimization objectives.

Table 1 Deterministic parameters and random variables associated with the illustrative example

Notation (units)	Mean	Coefficient of variation	Distribution type
a_o (mm)[a]	0.5	0.1	Lognormal
m[b]	3	-	Deterministic
C	2.3×10^{-12}[b]	0.3[c]	Lognormal
S_{re} (MPa)	20	0.1	Weibull[d]
N_{av}[d] (cycles/year)	1.0×10^{6}	0.1	Lognormal

Based on: [a] Chung et al. (2006); [b] BSI (2005); [c] Kim and Frangopol (2011); [d] Kim and Frangopol (2012)

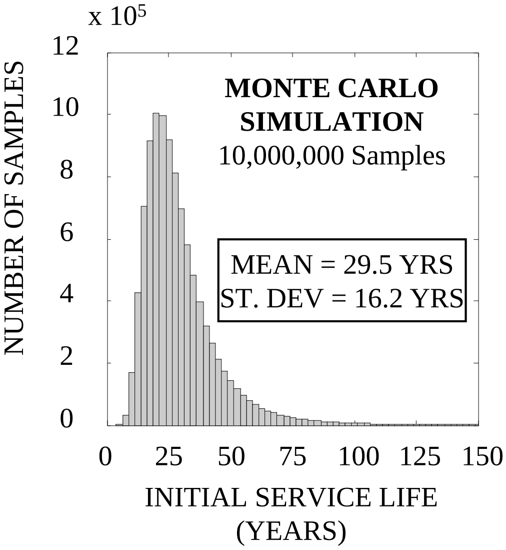

Figure 4 Histogram of the initial service life

A tri-objective optimization problem is formulated and solved using Genetic Algorithms (GAs). The ultrasonic technique is considered as the inspection method for fatigue crack detection. However, any other non-destructive inspection method can be used. The AE technique is considered as the crack monitoring methodology. The PoD parameters α and β associated with ultrasonic inspection are considered 0.122 and -0.305, respectively (Forsyth and Fahr 1998). In this example, the monitoring duration is assumed to be one day, one week, or six weeks, where the optimizer is responsible for selecting the optimal duration associated with scheduled monitoring actions. The parameters α and β associated with AE monitoring for six weeks are considered, based on Pollock (2007, 2010), as 0.801 and -0.491, while for monitoring periods of one week and one day, a reduction factor $R_{t_{md}}$ of 0.65 and 0.5, respectively, is applied to the *PoD* function as shown in Equation (6).

The optimization problem is formulated as follows

$$\text{Given} \quad N, \mathbf{C}, \boldsymbol{\alpha}, \boldsymbol{\beta} \; \textit{and} \; \text{PDF of } t_o \tag{11}$$

$$\text{Find} \quad \mathbf{t}_i, \; \mathbf{t}_{md,i}, a_r \tag{12}$$

$$\text{Such that} \quad t_i - t_{i-1} \geq 1.0 \; \textit{year} \tag{13}$$

$$\text{To} \quad \text{maximize } E\left[T\right], \text{ minimize } E\left[C^I\right], \text{ and minimize } E\left[C^F\right] \tag{14}$$

where $\mathbf{t}_i$ is a vector consisting of the design variables of intervention times, $\mathbf{t}_{md,i}$ is a vector consisting of the monitoring durations, $t_{md,i}$ is the monitoring time associated with the *i*th intervention and it is equal to zero for the case of inspection, t_o is the initial service life, a_r is the critical crack size for repair, *N* is the number of interventions, **C** is a vector consisting of the cost of inspection, monitoring, in-depth inspection, and repair. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are vectors consisting of *PoD* function parameters for different inspection and monitoring methods.

In this example, the cost of inspection is considered to be $15,000 while the monitoring cost consists of an initial cost of $15,000 and a running cost which increases with the increase in the monitoring duration ($1,000/week). The in-depth inspection cost and maintenance cost are assumed to be $15,000 and $50,000, respectively. Additionally, C_f is assumed $100,000.

Next, the tri-objective optimization problem is constructed and solved by using the Global Optimization Toolbox provided in version R2013 of MATLAB (MathWorks 2013). A Generic Algorithm with a population size 400 and maximum number of generations 250 is adopted to develop the Pareto-optimal solution set provided in Figure 5.

The Pareto front indicates that these are truly conflicting objectives where the expected service life cannot be maximized simultaneously with the minimization of expected life-cycle intervention costs and minimization of expected failure costs. Table 2 presents the design variables and objective function values for three intervention plans A, B, and C highlighted in Figure 5.

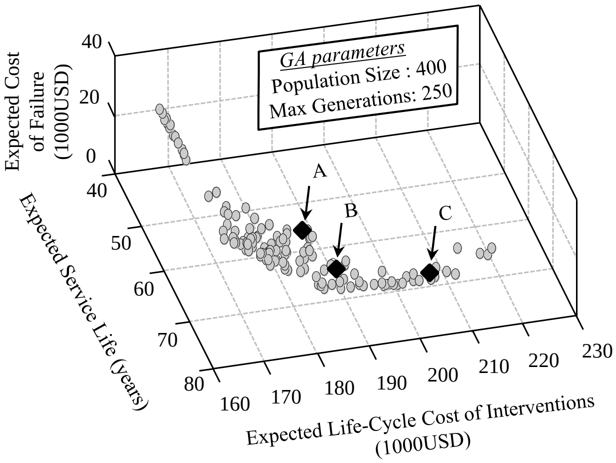

Figure 5 Pareto-optimal solution set for maximizing the expected service life, minimizing the life-cycle intervention cost, and minimizing the expected cost of faiure

Plans A and B implement acoustic emissions monitoring with a monitoring duration of 1 day for each intervention, while Plan C implements only ultrasonic inspections. Other solutions allow for mixed implementation of inspection/monitoring methods but are not shown here. All three plans are characterized by low expected failure costs but demonstrate the range of expected life and expected maintenance cost that can be taken, and the trade-off between them.

Table 2 Three optimum management plans shown in Figure 5 for the multi-objective optimization problem

Plan	Design variables				Objective Values		
	t_1^* (YR)	t_2^* (YR)	t_3^* (YR)	a_r (mm)	$E[T]$ (YR)	$E[C^I]$ (USD)	$E[C^F]$ (USD)
A	12	33	36	9.2	57.9	188×10^3	3.30×10^3
B	13	33	51	7.4	68.0	190×10^3	4.38×10^3
C	11	28	47	7.2	70.2	207×10^3	1.42×10^3

* Time approximated to the nearest year

In order for decision makers to determine the optimal management plan considering the conflicting objectives, they must first set acceptable thresholds for two of the three objectives and the front will provide the management plan which minimizes the third. For example, the decision maker may set a desired service life and acceptable failure cost threshold, and the front will provide the minimum repair cost and associated management plan.

6. CONCLUSIONS

This paper presented an approach for scheduling interventions along the life-cycle of a structural component under fatigue deterioration. The interventions included inspection, monitoring, and repair actions applied to damaged components. The ultrasonic technique is considered as the inspection method, while monitoring is assumed to be performed by using the acoustic emissions technique. However, any inspection or monitoring method can be used given the proper identification of the *PoD* model parameters. A tri-objective optimization problem is constructed and solved to identify the optimum inspection times, monitoring times and durations, and critical crack size for repair which simultaneously maximizes the expected service life, minimizes the interventions cost, and minimizes the expected failure cost. The proposed approach aids in establishing optimum and cost effective management solutions for deteriorating ships by providing the trade-offs between conflicting life-cycle management criteria.

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8. REFERENCES

Akpan, U.O., Koko, T.S., Ayyub, B., and Dunbar, T.E. (2002). "Risk assessment of aging ship hull structures in the presence of corrosion and fatigue." *Marine Structures*, 15(3), 211–31.

Barsom, J.M., and Rolfe, S.T., (1999). Fracture and fatigue control in structures: applications of fracture mechanics. Third Edition, American Society for Testing and Materials, West Conshohocken, PA.

British Standards Institution (BSI). (2005). Guidance on methods for assessing the acceptability of flaws in fusion welded structures. BS7910, London.

Chung, H., Manuel, L., Frank, K. (2006). "Optimal inspection scheduling of steel bridges using nondestructive testing techniques." *Journal of Bridge Engineering*, 11(3), 305-319.

Collette, M. (2005). "*Strength and reliability of aluminum stiffened panels*." A Thesis submitted for the Degree of Doctor of Philosophy, School of Marine Science and Technology, Faculty of Science, Agriculture and Engineering, University of Newcastle, UK.

Fisher, J.W., Kulak, G.L., and Smith, I.F. (1998). "*A fatigue primer for structural engineers*." National Steel Bridge Alliance, Chicago, IL

Forsyth, D., and Fahr, A. (1998). "An evaluation of probability of detection statistics." *Proc., RTO-AVT Workshop on Airframe Inspection Reliability under Field/Depot Conditions, NATO Research and Technology Organization*, Neuilly-Sur-Seine, Cedex, France.

Frangopol D.M. (2011). "Life-cycle performance, management, and optimization of structural systems under uncertainty: accomplishments and challenges." *Structure and Infrastructure Engineering*, 7(6), 389-413.

Frangopol, D.M., and Soliman, M. (2015). "Evaluation and prediction of damage to ship structures under uncertainty," Chapter 18 in *Handbook of Damage Mechanics: Nano to Macro Scale of Materials and Structures* (G.Z. Voyiadjis, ed.), Springer, New York, 565-588.

Glen, I. F., Dinovitzer, A., Paterson, R. B., Luznil, L., and Bayley, C. (1999). "*Fatigue-resistant detail design guide for ship structures*." Ship Structure Committee Rep. No. SSC–405, Ship Structure Committee, Washington, DC.

Guedes Soares, C., and Garbatov, Y. (1999a). "Reliability of maintained, corrosion protected plate subjected to non-linear corrosion and compressive loads." *Marine Structures*, 12, 425–445.

Guedes Soares, C., and Garbatov, Y. (1999b). "Reliability based fatigue design of maintained welded joints in the side shell of tankers." *European Structural Integrity Society*, 23, 13-28.

Kim, S., and Frangopol, D.M. (2011). "Optimum inspection planning for minimizing fatigue damage detection delay of ship hull structures." *International Journal of Fatigue*, 33(3), 448-459.

Kim, S., and Frangopol, D.M. (2012). "Probabilistic bicriterion optimum inspection/monitoring planning: Application to naval ships and bridges under fatigue." *Structure and Infrastructure Engineering*, 8(10), 912-927.

Kim, S., Frangopol, D.M., Soliman, M. (2013). "Generalized probabilistic framework for optimum inspection and maintenance planning." *Journal of Structural Engineering*, 139(3), 435-447.

Kwon, K., and Frangopol, D.M. (2012). "Fatigue life assessment and lifetime management of aluminum ships using life-cycle optimization." *Journal of Ship Research*, 56(2), 91–105.

MathWorks (2013). "*Global optimization toolbox 3.2.2 user's guide*," The MathWorks Inc., Natick, MA.

Paris, P.C., and Erdogan, F.A. (1963). "Critical analysis of crack propagation laws." *Journal of Basic Engineering*, 85(Series D), 528–534.

Pollock, A. (2007). "Probability of detection for acoustic emission." *Journal of Acoustic Emission*, 25, 231-237.

Pollock, A. (2010). "A POD model for acoustic emission-discussion and status." In *Review of Progress in Quantitative Nondestructive Evaluation*, Vol. 209, eds. D.O. Thompson and D.E. Chimenti, AIP Publishing, Melville, NY, 1927-1933.

Soliman, M., Frangopol, D.M., Kim, S. (2013). "Probabilistic optimum inspection planning of steel bridges with multiple fatigue sensitive details." *Engineering Structures*, 49, 996-1006.