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Reliability analysis of corroding pipelines by enhanced Monte Carlo simulation

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ABSTRACT

The present paper addresses reliability analysis of corroding pipelines considering also system reliability effects. The analysis is performed by utilization of enhanced Monte-Carlo simulation methods which have been found to be very efficient for quantification of system reliability in the case of multiple components with arbitrary correlation levels. The examples which are studied in the paper comprise systems with corrosion defects which are both independent and correlated.

1. Introduction

Corrosion of ageing pipelines is found to be a significant problem both onshore and within the subsea area. In order to determine the remaining time in service for such pipelines, it is required that deterministic capacity models are established as well as associated probability models for the key parameters. Having obtained these models, a proper reliability analysis and risk assessment can be performed.

The importance of this issue is reflected by the large number of associated publications in the existing literature. Some examples of probabilistic reliability analyses are found in the papers by Ahammed [2], Ahammed & Melchers [3], Caleyo et al. [5], Pandey [8], Lee et al. [10], Li et al. [11,12], Teixeira et al. [19], Santosh et al. [20], Zhou [26] and Hasan et al. [7]. Examples of relevant historic and more recent design guidelines are respectively ANSI/ASME B31G [1] and DNV [6].

As discussed in more detail below, there are significant differences between the applied probabilistic models which are employed in the various reliability analyses that have been performed. This applies in particular to the statistical parameters which are employed for characterization of the internal pressure and the corrosion defects. Furthermore, in most cases a single corrosion defect is analysed. Only brief comments are usually given with respect to the system modeling that will be required in order to account for multiple defects.

In a few cases system analyses are performed by means of Ditlevsen bounds for estimation of failure probability for series systems (see e.g. Melchers [13]. A more elaborate study of the effect of correlation between component failure events and system reliability was performed by Xie [22] mainly based on an analytical approach. Results from more recent research dealing with this topic are found e.g. in Qijan et al. [18], Zhang [23], Zhang and Zhou [24], Zhou et. al. [25]; and Zhou [27]. The latter of these studies employs a stochastic process model for the pressure time history and for the damage accumulation. Markov models for the same quantities were applied e.g. by Timashev and Bushinskaya [21]. In the present paper, system modeling is focused upon both with respect to method of analysis and computational results.

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2. Method for system reliability analysis

2.1. Basic formulation

The enhanced Monte Carlo (MC) based method for estimation of system reliability which is applied for the present study is further described in Naess et al. [15]. The aim of this method is to reduce computational cost while maintaining the advantages of crude MC simulation. This applies in particular when dealing with complex systems. The key idea is to exploit the regularity of the tail probabilities. Based on results obtained from small Monte-Carlo samples for moderate levels of reliability this regularity enables prediction of far tail failure probabilities.

The motivation behind this approach is that systems with multiple and complex failure modes or limit states are often exceedingly difficult to analyze using traditional methods of structural reliability. On the other hand, even if direct MC does not suffer from this problem, it is computationally heavy for small probabilities. This gives rise to the idea of sampling in a different and less reliable range and performing a statistical tail extrapolation. A related idea is presented by Bucher [4].

The fundamentals of the Naess et al. [15] method are as follows. A safety margin $M = G(X_1,, X_n)$ expressed in terms of n basic variables, is extended to a parameterized class of safety margins using a scaling parameter λ ($0 \le \lambda \le 1$):

$$\mathrm{M}(\lambda) = \mathrm{M} - (1-\lambda)\mathrm{E}(\mathrm{M}) \tag{1}$$

Under certain conditions related to the distributions of the basic random variables Naess et al. [15], the failure probability is then assumed to behave as follows:

$$p_f(\lambda) = Prob\,(M(\lambda) \le 0) \underset{\lambda \to 1}{\approx} q(\lambda) exp\{-a(\lambda-b)^c\} \tag{2}$$

where the function $q(\lambda)$ is slowly varying compared with the exponential function $exp\{-a(\lambda-b)^c\}$. In practice, $q(\lambda)$ is therefore replaced by a constant q for $\lambda > \lambda_0$ for a suitable choice of λ_0. Clearly, the relevant failure probability $p_f = p_f(1)$ can then be obtained from values of $p_f(\lambda)$ for $\lambda_0 < \lambda < 1$ if the parameters q, a, b, c have been determined. It is clearly easier to estimate the (larger) failure probabilities $p_f(\lambda)$ for $\lambda < 1$ than the target value itself, since they require fewer simulations to achieve the same level of accuracy. Fitting the parametric form $q\,exp\{-a(\lambda-b)^c\}$ for $p_f(\lambda)$ to the estimated values would then provide an estimate of the target value by extrapolation. The viability of this approach is demonstrated by both analytical and numerical examples e.g. in Naess et al. [15–17].

2.2. System reliability analysis

Using Monte Carlo methods for system reliability analysis has several attractive features, the most important being that the failure criterion is relatively easy to check almost irrespective of the complexity of the system. In order to limit the amount of computational effort that may be involved, it is hence useful to extend the above approach to systems.

Let $M_j = G_j(X_1, \ldots, X_n),\ j = 1, \ldots, m,$ be a set of m given safety margins expressed in terms of n basic variables. Then the parameterized class of safety margins $M_j(\lambda) = M_j - (1-\lambda)E(M_j),\ j = 1, \ldots, m,$ is then introduced. For a given value of λ, the series system reliability expressed in terms of the failure probability can then be written as,

$$p_f(\lambda) = Prob\left(\cup_{j=1}^{m}\{M_j(\lambda) \le 0\}\right), \tag{3}$$

while for parallel systems,

$$p_f(\lambda) = Prob\left(\cap_{j=1}^{m}\{M_j(\lambda) \le 0\}\right). \tag{4}$$

In general, any system can be written as a series system of parallel subsystems. The failure probability would then be given as,

$$p_f(\lambda) = Prob\left(\cup_{j=1}^{l}\ \cap_{i\,\varepsilon C_j}\{M_i(\lambda) \le 0\}\right). \tag{5}$$

Here, each C_j is a subset of $\{1, \ldots, m\},$ for $j = 1, \ldots, l.$ The C_j s denote the index sets defining the parallel subsystems. We then make the assumption that $p_f(\lambda)$ can also be represented as in Eq. (2) for the system reliability problems.

2.3. Implementation

The method to be described in this section is based on the assumption expressed by Eq. (2). For practical applications it is implemented in the following form:

$$p_f(\lambda) \approx q \cdot \exp\{-a(\lambda-b)^c\}, \tag{6}$$

expressed in terms of four parameters q, a, b, c, for $\lambda_0 \le \lambda \le 1$, for a suitable value of λ_0. It is therefore necessary to identify a suitable range forλ so that the right hand side of Eq. (6) represents a fairly good approximation of $p_f(\lambda)$ for $\lambda \in [\lambda_0, 1]$.

For a sample of size N of the vector of basic random variables $\boldsymbol{X} = (X_1, \ldots, X_n)$, let $N_f(\lambda)$ denote the number of samples in the failure domain of the system. The corresponding estimate of the failure probability is then

$$\widehat{p}_f(\lambda) = \frac{N_f(\lambda)}{N}. \tag{7}$$

The coefficient of variation C_v of this estimator is

$$C_v\left(\widehat{p}_f(\lambda)\right) = \sqrt{\frac{1-\widehat{p}_f(\lambda)}{\widehat{p}_f(\lambda)N}}. \tag{8}$$

A fair approximation of the 95% confidence interval for the value $\widehat{p}_f(\lambda)$ can be obtained as $\mathrm{CI}_{0.95}(\lambda) = (C^-(\lambda),\ C^+(\lambda))$, where

$$C^{\pm}(\lambda) = \widehat{p}_f(\lambda)\left(1 \pm 1.96 C_v\left(\widehat{p}_f(\lambda)\right)\right) \tag{9}$$

Assuming now that we have obtained empirical Monte Carlo estimates of the failure probability, the problem then becomes that of optimal use of the information available.

The problem of finding the optimal values of the parameters $q,\ a,\ b,\ c$ is solved by optimizing the fit on the log level by minimizing the following mean square error function with respect to all four arguments Naess and Gaidai [14],

$$\mathrm{F}(q,a,b,c) = \sum_{j=1}^{M} w_j \left(\log \widehat{p}_f(\lambda_j) - \log q + a(\lambda_j - b)^c\right)^2 \tag{10}$$

where $0 < \lambda_1 < \ldots < \lambda_M < 1$ denotes the set of λ values where the failure probability is empirically estimated. The w_j denote weight factors that put more emphasis on the more reliable estimates.

A Levenberg–Marquardt least squares optimization method [28] is applied for the present minimization. Although this method generally works well, it may be simplified by exploiting the