Reliability assessment of deteriorating structures: Challenges and (some) solutions

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ABSTRACT: The assessment of deteriorating structural systems has been one of the major applications of probabilistic analysis and structural reliability theory. Nevertheless, looking back on over 40 years of research and development in this area, the outcome has been mixed. While a lot of progress has been made, important questions and challenges still have not been answered. Structural reliability methods still play a minor role in the management of existing deteriorating structures in practice. There are encouraging signs, e.g. the development of standards and guidelines for existing structures that rely at least partly on structural reliability methods. But there remain significant open challenges to the structural reliability community, some of which I discuss in this contribution.

1 INTRODUCTION

The assessment of deteriorating structural systems has been one of the major applications of probabilistic analysis and structural reliability theory, for multiple reasons. Firstly, with the exception of fatigue, the quantitative assessment of deterioration is not considered in current codes based on the partial safety factor format. Hence, it is challenging to demonstrate the reliability of deteriorating structural systems with standard (semi-probabilistic) safety concepts alone (Faber 2000, JCSS 2001, Melchers 2001, Ellingwood 2005). Secondly, deterioration is often assessed for existing structures in which damages have been observed. For such structures, data is typically available from past inspections, monitoring or tests performed during the construction and operation of the structure. These data can be used to update the parameters of structural models, deterioration models or the reliability itself. Such an integration is best performed through a probabilistic analysis. Thirdly, in addition to deterioration, existing structures are often subject to changes in demand or loss of capacity, which may cause noncompliance of the structure with current code requirements. In some cases, a probabilistic assessment can demonstrate that a structure is nevertheless safe for future usage.

All these applications of structural reliability require a proper probabilistic description of the structural model and its parameters. A major challenge thereby is that the data available from existing structures cannot be explained with the simple models assumed in classical structural design and simple reliability analysis. Instead, the data reflect the real behavior of the structure and the spatial variability of the parameters. For this reason, the assessment of existing structures often necessitates more sophisticated structural and probabilistic models than the design of new structures. Thereby, the proper modeling choices are crucial, as overly simple models can lead to entirely wrong results, whereas overly complicated models lead to an unnecessary effort for analysis and – because of the difficulties in reliability analysis – are also more error-prone.

The challenges associated with the modeling are related to:

- Deterioration modeling
- Structural system modeling
- Probabilistic modeling
- Dependence modeling
- Modeling of inspection and monitoring

In this contribution, I review these challenges and outline strategies for handling the modeling in Sections 3 to 6. The aim is to discuss when simple models are sufficient, and when more advanced models of the structural system and spatially variable parameters are required. The selected modeling approach has direct implications on the computational aspect of the reliability analysis. I will highlight recent computational developments that facilitate the application of advanced models in engineering practice.

Finally, main challenges in the assessment of deteriorating structures are associated with the management and the organization of owners and operators. These include data and model availability, development of codes and standards as well as general organizational aspects. I will address these throughout the manuscript.

The paper starts out with the presentation of an idealized example and a review of the basic quantities in the reliability assessment of structures over their service life (Section 2). This example should allow the reader to follow and – if desired – to replicate some of the analyses presented in this paper.

2 RELIABILITY ANALYSIS OF DETERIORATING STRUCTURES

2.1 *An idealized structure*

To illustrate the concepts, methods and challenges associated with the assessment of deteriorating structures, I introduce a highly idealized example, which nevertheless features most of the relevant aspects of a real-life structural system. The structural system, shown in Figure 1, is a frame structure with ideal plastic material behavior. It has been studied in multiple text books and papers previously, without considering deterioration (Madsen et al. 1986, Der Kiureghian 2005). The frame is characterized by the plastic moment capacities at locations $1-5$. There are two loads: the permanent load V and the time-variant load H. The latter is described by the distribution of its annual maxima H_j, with the index j denoting the year.

The structure is subject to deterioration, which is modeled at the element level $i = 1, \dots, 5$ as:

$$D_i(t) = 1 - \Phi\left(\frac{t - B_i}{0.2B_i}\right) \tag{1}$$

Φ is the cumulative distribution function (CDF) of the standard normal distribution, B_i is the deterioration model parameter.

The resulting moment capacity $R_i(t)$ of element i at time t is

$$R_i(t) = M_i \cdot D_i(t) \tag{2}$$

with M_i being the initial moment capacity.

The occurrence of the three failure mechanisms depicted in Figure 1 in year j is described by the following limit state functions (Madsen et al. 1986):

$$g_{a,j}(\mathbf{X}) = R_1(t_j) + R_2(t_j) + R_4(t_j) + R_5(t_j) - 5H_j \tag{3}$$

$$g_{b,j}(\mathbf{X}) = R_2(t_j) + 2R_3(t_j) + R_4(t_j) - 5V \tag{4}$$

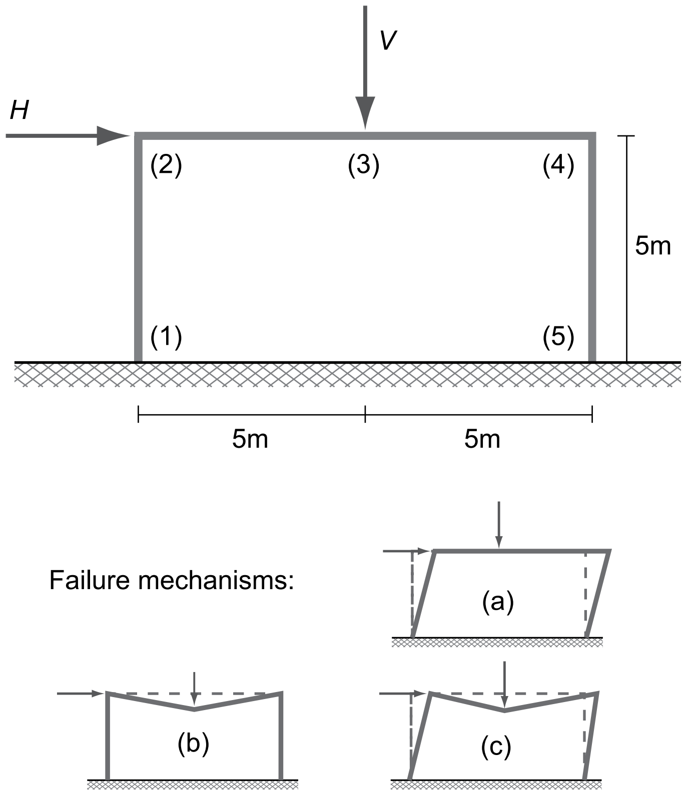

Figure 1: Frame structure and its three main failure mechanisms.

$$g_{c,j}(\mathbf{X}) = R_1(t_j) + 2R_3(t_j) + 2R_4(t_j) + R_5(t_j) - 5H_j - 5V \tag{5}$$

wherein t_j is the time associated with the jth year. If the structure is installed at time $t = 0$, then it is simply $t_j = j$.

The event of failure of the structural system during year j is then described by the system limit state function:

$$g_j(\mathbf{X}) = \min[g_{a,j}(\mathbf{X}), g_{b,j}(\mathbf{X}), g_{c,j}(\mathbf{X})] \tag{6}$$

with failure in year j defined as:

$$F_j = \{g_j(\mathbf{X}) \leq 0\} \tag{7}$$

The probability of failure of the undamaged structure in the first year of service (with $R_i \simeq M_i$) is $\Pr(F_0) = 9.95 \times 10^{-4}$.

The event of failure up to time t_j is defined as

$$F(t_j) = F_1 \cup F_2 \cup \ldots \cup F_j \tag{8}$$

The corresponding probability of failure of the structure up to time t_j is

$$\Pr[F(t_j)] = \Pr(F_1 \cup F_2 \cup \ldots \cup F_j) \tag{9}$$

$\Pr[F(t_j)]$ is the quantity that should be utilized for the assessment of the reliability. Unfortunately, this corresponds to a system reliability problem among the failure events in different years (in addition to the system reliability problem describing failure in each

Table 1: Stochastic model of the example structure.

Parameter	Unit	Distribution	Mean	St. dev.
H_j (annual max.)	kN	Gumbel	50	20
V	kN	gamma	60	12
$M_1 - M_5$	kNm	lognormal	200	30
$B_1 - B_5$	yr	lognormal	100	50
ρ_M	–	det.	0.3	
ρ_A	–	det.	0.6	

year, Eq. 6). In many instances, therefore, the probability of Eq. 9 is approximated by one of the following bounds:

$$\Pr(F_j) \leq \Pr[F(t_j)] \leq 1 - \prod_{i=1}^{j}[1 - \Pr(F_i)] \qquad (10)$$

Efficient solutions to computing the exact $\Pr[F(t_j)]$ are presented in (Straub et al. 2019).

2.2 *Lifetime reliability*

To assess the reliability of structures over their lifetime, the reliability is best expressed by the probability of failure up to time t, which is equal to the CDF of the time to failure T_F (Barlow and Proschan 1996, Rausand and Høyland 2004):

$$\Pr[F(t)] = F_{T_F}(t) = \Pr(T_F \leq t) \qquad (11)$$

The reliability at time t is

$$Rel(t) = 1 - \Pr[F(t)] \qquad (12)$$

The probability density function (PDF) of the lifetime T_F is

$$f_{T_F}(t) = \frac{dF_{T_F}(t)}{dt} = -\frac{dRel(t)}{dt} \qquad (13)$$

The hazard function (failure rate) is defined as

$$h_F(t) = \frac{f_{T_F}(t)}{Rel(t)} \qquad (14)$$

The probability of failure of the example structure is shown in Figure 2; the corresponding hazard function is shown in Figure 3. The effect of the deterioration is evident. Without deterioration, the hazard function of the structure is slightly decreasing over time, from 10^{-3} at time $t = 0$ to $0.89 \cdot 10^{-3}$ at time $t = 50$yr. This is caused by a *proof load effect*: Survival at earlier years is an indication that the structure has a certain minimum capacity and that the permanent load V is not excessively large.

Note that the probability of failure of this structure is artificially inflated; some effects are more clearly visible at large probability values. Most real structures have much smaller failure probabilities.

The risk associated with structural failure over the lifetime of the structure is a function of the lifetime PDF f_{T_F}:

$$Risk = \int_0^\infty C_F \exp[-\gamma t] f_{T_F}(t) dt \qquad (15)$$

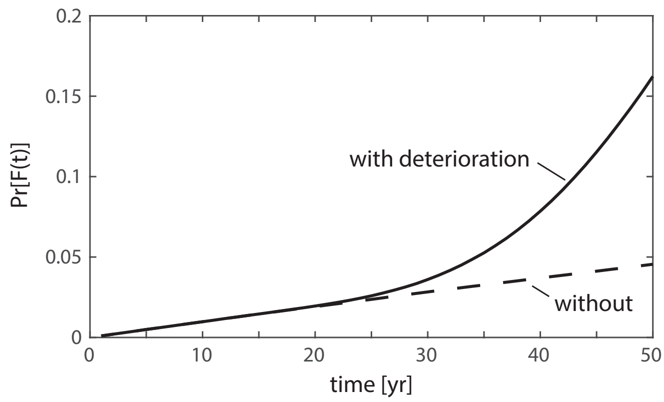

Figure 2: Probability of failure of the example structure.

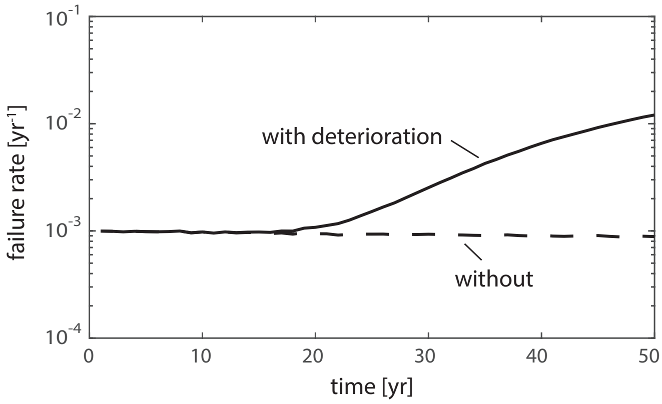

Figure 3: Hazard function (failure rate) of the example structure.

wherein C_F is the cost associated with a failure and γ is the discount rate. $Risk$ is the net present value of the risk.

Eq. 15 assumes that the structure is utilized until failure. If only a finite service lifetime T_{SL} is considered, the upper limit of the integral is replaced by T_{SL}. Figure 4 shows the net present risk of the example structure in function of the considered service life period T_{SL}, with $\gamma = 2\%$ and $C_F = 10^6$. It is evident that the possibility of failures beyond 100yr in the future does not significantly affect the net present value of the risk; in the case of the non-deteriorating structure it is $Risk(100\text{yr}) = 38 \cdot 10^3$ vs. $Risk(\infty) = 42 \cdot 10^3$. The reason lies in the discounting of future failure costs to $t = 0$.

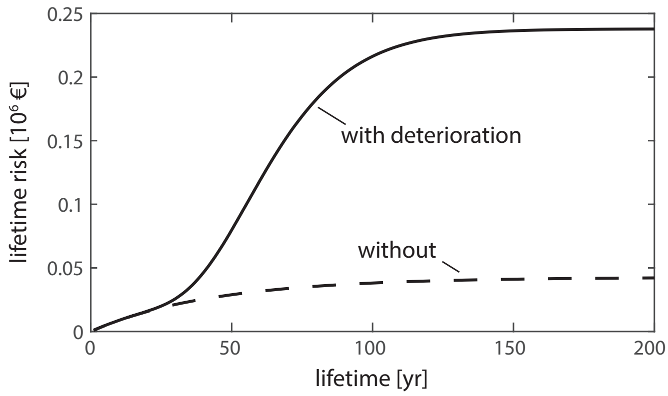

Figure 4: Lifetime risk (net present value) of the example structure in function of the intended service life.

A proper life-cycle costing should also consider obsolescence and replacement of the structure (Rackwitz 2000). However, almost all studies on optimal asset integrity management ignore the possibility of obsolescence. Also, estimating the probability of obsolescence appears challenging, since it requires predictions on future technological progress and socioeconomic developments.

2.3 *The example structure vs. real life structures*

In the following sections, the various aspects of assessing the system reliability of deteriorating structures will be discussed. The example structure will be utilized to illustrate points made in the discussion. The idealized example structure has multiple convenient features not encountered in real-life applications, as every engineer who has worked on the assessment of deteriorating structures can testify. I will address these features in the subsequent sections. My aim is to demonstrate that the reduction to an idealized model can often provide the solution path for more complex problems. But I will also show that to some challenges no easy solutions are available.

3 DETERIORATION MODELING

3.1 *Model availability and accuracy*

There is a substantial amount of literature on stochastic deterioration models for structures (Lin and Yang 1985, DuraCrete 1998, Stewart and Rosowsky 1998, Melchers 1999a, Frangopol et al. 2004). Nevertheless, good deterioration models exist only for few common phenomena, in particular for fatigue in metallic structures and for reinforcement corrosion in RC structures. And even in these areas, the prediction ability of the models can be quite poor outside of laboratory conditions. In one of the few examples of in-service validation of deterioration models, Aker Offshore Partner (1999) compare predictions of fatigue life with observed fatigue crack rates in offshore steel structures. Their conclusions are rather discouraging, indicating a limited predictive power of fatigue models. Figure 5 shows results from this study, in which the observed frequencies of fatigue cracks are summarized for groups of fatigue details with the same predicted fatigue reliability at the time of inspection. The data shown in Figure 5 is from older structures built prior to 1975. Results from the same study indicate that the observed frequency of fatigue cracks in newer structures is significantly lower, yet the predictive power of the fatigue model is not better.

For many deterioration phenomena, quantitative predictive models are lacking entirely. For example, in Germany significant resources are spent on ensuring the reliability of prestressed concrete bridges built mainly in the 1960s and 70s that are subject to stress

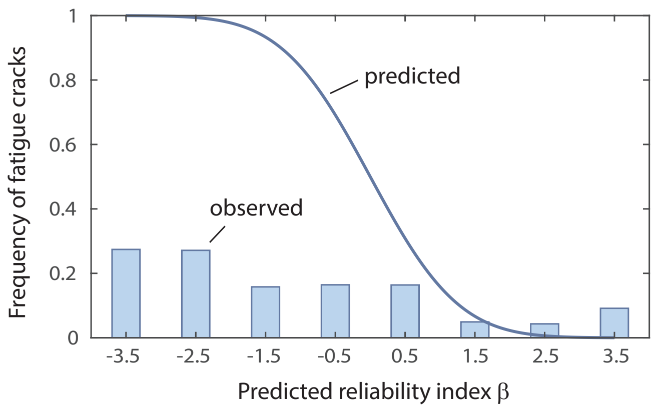

Figure 5: Observed frequency of fatigue cracks in structural details in function of the calculated fatigue reliability of these details. The predicted frequency is the one according to theory, i.e. $\Phi(-\beta)$. Figure adapted from (Aker Offshore Partner 1999).

corrosion cracking (SCC). Because no suitable predictive model for SCC exists, authorities are required to take a highly conservative approach based on substantial inspection efforts (Lingemann et al. 2010).

Overall, stochastic modeling of deterioration for the purpose of assessing the reliability of a structure is challenging. The associated uncertainty signifies that in most applications, models can give useful predictions only if accompanied by data collection through tests, inspections and monitoring. However, models are necessary for making any kind of predictions, and despite trials to do otherwise, it is doubtful a quantitative demonstration of the reliability of a deteriorating structure is possible without an underlying deterioration model. The increased availability and quality of monitoring and other type of data provides an opportunity to develop more realistic deterioration models in the future. For this to happen, it is however important that infrastructure owners and operators define and impose standards for the collection of such data.

3.2 *Deterioration modeling at the system level*

With few exceptions, deterioration in structural systems is modeled at the element level, in analogy to the example structure of Section 2.1. This is due to the uniqueness of structures, which does not allow for models to be easily transferred from one structure to another. Exceptions to the rule are some empirically-based models that are based on past inspection data, e.g. models utilized in bridge management systems (BMS) (Scherer and Glagola 1994, Thompson et al. 1998). A main limitation to developing such empirical models has been the lack of high-quality data. Existing data comes from traditional bridge inspections, which suffer from reporting standards that are not aimed at developing deterioration models. For example, in most cases, only the degree of damages in a part of the structure is reported, often without systematically noting the type of damage nor the mechanism causing it. Furthermore, the assessment by inspectors has a substantial subjective component and has also shown to be subject to significant uncertainty and variability (Phares et al. 2001).

Nevertheless, empirical models both at the subsystem and system level are likely to improve in the future. In particular efforts of infrastructure owners and operators to implement BIM (Building Information Management) standards should substantially improve the data collection, as is the progress in sensor, monitoring and communication technology.

4 STRUCTURAL SYSTEM MODELING

Since deterioration is typically modeled at the element level, a model of the structural system is necessary for understanding the effect of deterioration on the structural reliability. In the following, different approaches to handle this challenge are presented, in the order of increasing accuracy and complexity.

4.1 *Limiting the analysis to element failure events*

In Eurocode, and most other structural codes, the system reliability is not modeled explicitly. Instead, it is required that all structural elements comply with the reliability requirement, by demonstrating compliance with the design limit state for each cross section. In many cases, this is a conservative approach, but for new-built structures the approximation is often justified by the difficulty and cost of a more realistic system model.

The example structure of Section 2.1 is ductile and hence has significant reserves beyond yielding of the first member, as demonstrated in the following. If failure at the element level is defined as reaching the plastic limit (in accordance with a static equilibrium approach as used in Eurocode), the corresponding limit state functions are:

$$g_{e,i,j}(\mathbf{X}) = R_i(t_j) - |M_{S,i}(\mathbf{X}, j)| \tag{16}$$

wherein $M_{S,i,j}$ is the maximum resulting moment at location i in year j. The stiffness of the structure is constant throughout the structure and is described by the parameters $E = 200\text{GPa}$, $A = 0.02\text{m}^2$ and $I = 10^-4\text{m}^4$. With these parameters, a linear-elastic structural analysis results in the moments as follows:

$$M_{S,1,j} = 1.56\text{m} \cdot H_j - 0.5\text{m} \cdot V_j \tag{17}$$

$$M_{S,2,j} = -0.94\text{m} \cdot H_j + 1\text{m} \cdot V_j \tag{18}$$

$$M_{S,3,j} = 1.5\text{m} \cdot V_j \tag{19}$$

$$M_{S,4,j} = -0.94\text{m} \cdot H_j - 1\text{m} \cdot V_j \tag{20}$$

$$M_{S,5,j} = 1.56\text{m} \cdot H_j + 0.5\text{m} \cdot V_j \tag{21}$$

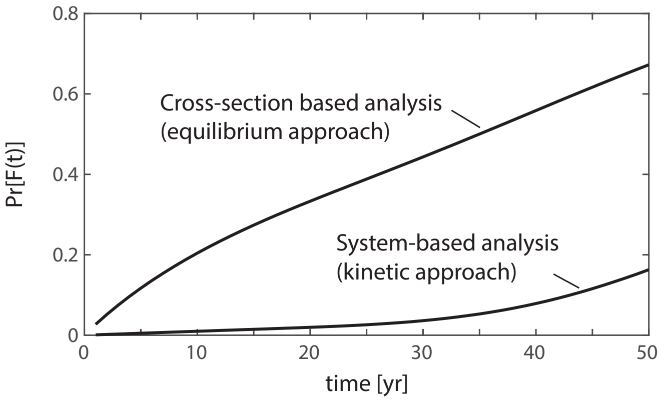

Figure 6: Probability of system failure computed with an element-based model in accordance with the classical design methodology in Eurocode, compared to the probability of failure evaluated with a system-based model (the same as in Figure 2).

If failure of the structural system is defined as the violation of any of the resulting 5 limit states, a corresponding system reliability estimate can be computed. The limit state functions $g_{e,i,j}(\mathbf{X})$ give significantly lower values than the ones describing the failure mechanisms (Eqs. 3-5). Therefore, the static equilibrium approach results in much higher probability of failure estimates than the system analysis approach of Section 2.1, which corresponds to a kinematic limit analysis. Figure 6 compares the probabilities of failure as computed with these two approaches. Assessing system performance through Eq. 16 can therefore be highly conservative. Such a model is nevertheless utilized in the assessment of existing and deteriorating structures because it complies with the safety format of common standards and is readily implemented with standard software tools, e.g. (Mix 2016).

4.2 *Full system reliability analysis*

A system reliability analysis, as it is performed on the example structure in Section 2.1, is not commonly applied for the assessment of structures in practice. In research, such analyses are performed and there seems to be no fundamental difficulty in performing them, even if some challenges remain. In practice, these analyses have been hindered by the significant computational demands and the practical difficulties associated with the need of coupling a structural analysis model with a structural reliability code. Today's computer performance and the large number of available structural reliability software solutions alleviate these problems.

Another hindrance in performing an integrated system-wide analysis lies in the analysis workflow, which is still mostly element-based. The deterioration is evaluated at the element level (e.g. fatigue lives are calculated for structural details), and it is often preferable to assess the reliability element by element. In principle, such an approach can also ensure the reliability of the system, but it necessitates that reliability acceptance criteria at the element level are de-

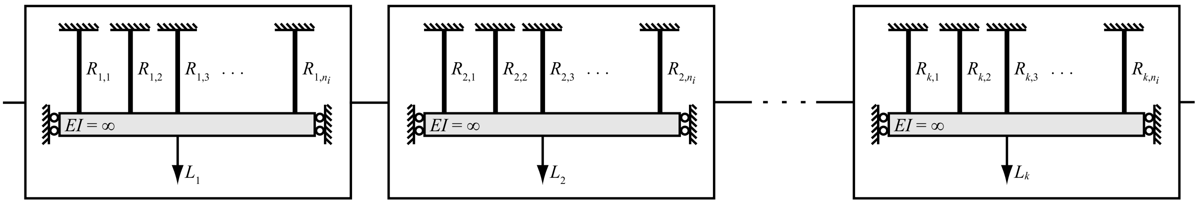

Figure 7: System model of (Straub and Der Kiureghian 2011) for determining reliability acceptance criteria at the structural element level based on the $n-1$ redundancy.

rived, which are consistent with the requirements to the structural system. This is outlined in the next section.

4.3 *Deriving reliability requirements at the element level based on a simplified representation of redundancy by an $n-1$ analysis*

For some types of deterioration in structures, e.g. fatigue, it can be sufficiently accurate to consider an element as either fully intact or completely failed. In this case, the element performance can be modeled at the system level by a Bernoulli random variable with binary outcome states. On this basis, it is possible to derive reliability acceptance criteria at the element level based on overall reliability levels at the system level (Straub and Der Kiureghian 2011).

To this end, simplified system models were proposed in the past for the analysis of offshore steel structures (Moan 1999, Faber et al. 2000, Moan 2005, Straub and Faber 2005a). They are based on evaluating the reduction in overall system capacity upon failure of individual elements and then estimating the probability of system failure conditional on these failures. These analyses are in analogy to $n-1$ contingency analyses, which are commonly applied to test system redundancy, in structures (e.g., Frangopol and Curley 1987) as well as other engineering systems, e.g. power grids (Stott et al. 1987).

A measure to assess the element importance in this way is the probability of failure of the structure with element i removed[1]: $\Pr(F_{0,-i})$. This quantity is computed for the non-deteriorated structure, i.e. all members other than i are intact.

To understand the redundancy, $\Pr(F_{0,-i})$ should be compared to the intact reliability. This can be achieved with the Single Element Importance (SEI) measure, with $\Pr(F_0)$ being the probability of failure of the intact structure (Straub and Der Kiureghian 2011):

$$SEI_i = \Pr(F_{0,-i}) - \Pr(F_0) \tag{22}$$

For the example system, the resulting SEI are given in Table 2. Element 3 is the one with the highest SEI, hence it contributes most to the overall failure probability.

Table 2: Element importance in the example structure.

Element i	1	2	3	4	5
$\Pr(F_{0,-i})$	0.010	0.009	0.128	0.051	0.010
$\Pr(F_{0,-i})/\Pr(F_0)$	10	9.5	129	51	10
SEI_i	0.009	0.008	0.127	0.050	0.009

To address the effect of element failure on the system reliability, the following model has been applied frequently:

$$\Pr[F(t)] \approx \Pr(F_0) + \sum_{i=1}^{n} \Pr(F_{0,-i}) \cdot \Pr[F_{e,i}(t)] \tag{23}$$

$F_{e,i}(t)$ is the event of fatigue failure of element i up to time t. The advantage of this system model is its simplicity, as it does not require to consider element interactions. Hence the model allows a treatment of deterioration reliability at the element level. The model has e.g. been used in the reassessment of offshore steel platforms (Moan 1999, Faber et al. 2000, Moan 2005).

In (Straub and Der Kiureghian 2011) we showed that the model of Eq. 23 can be oversimplifying in structures with significant redundancy, because it neglects the interactions and dependence among elements. Critically, it can lead to strong overestimation of the reliability of a damaged structure.

To mitigate the problem, without losing modeling and computational advantages, we proposed to extend the model by construction of a conceptual structure, in which the structural element is part of one or multiple Daniels systems that are connected in series, as shown in Figure 7. The Daniels system is the simplest instance of load sharing structures (Gollwitzer and Rackwitz 1990). For each element, we estimate the number of elements in the associated Daniels system and the total number of Daniels systems in series, based on the $\Pr(F_{0,-i})$ values and the reliability of the undamaged structure. The model of Figure 7 can be evaluated cheaply, hence it is suitable for determining the reliability requirements for each element, which ensure that the overall system has sufficient reliability.

The model was examined in (Straub and Der Kiureghian 2011) by considering example structures with a target reliability of $\beta = 4.2$. When determining

[1] Note that this is not identical to the conditional probability of structural failure given failure of element i. In computing this conditional failure probability, one has to consider the stochastic dependence among the elements, which is not included in the definition used here.

the necessary element reliabilities based on the simple model of Eq. 23, the resulting structural system reliability achieved is in the range of $\beta = 2.5 - 3.8$, well below the target of 4.2. With the model of Figure 7, the system reliability is $\beta = 4.0 - 4.1$.

4.4 *Research needs*

In the 1980-90s, substantial research efforts were made towards improving structural system reliability models (an overview is provided in Melchers 1999b). Since the 2000s, this has pretty much seized to be an active field of research, with a few exceptions (e.g., Lee and Song 2011). Solutions have been found for specific applications, e.g. as discussed above. But generally satisfactory solutions, in particular approaches that can be included in standard and codes, are still lacking. Current design codes do not rigorously address the topic. For example, Eurocode 0 is mostly based on demonstrating the reliability at the cross-section level as in Section 4.1 above. Structural redundancy is addressed only qualitatively and reliability targets are not consistent at the structural system level. These considerations were explicitly excluded at the time of writing the code (DIN 1981). However, the currently ongoing revision of the Eurocode does not improve upon this situation, due to the lack of suitable approaches that lend themselves to codification. For deteriorating structures this is especially critical.

5 DEPENDENCE AND CORRELATION IN STRUCTURAL CONDITION AND PERFORMANCE

Deterioration processes at different locations in a structure are mutually dependent. In particular, variably and uncertain common influencing factors cause such dependence. For example, the same material and execution quality is encountered throughout a structure; the system as a whole is subject to the same load; and the same maintenance regime is applied for the entire structure. Only a limited number of studies have investigated these effects, but they show clear evidence of such dependences (e.g., Vrouwenvelder 2004, Li et al. 2004, Malioka et al. 2006, Luque et al. 2017).

Dependence among deterioration effects at different locations of the structure is relevant for two reasons: (a) In redundant systems, stochastic dependence among element capacities reduces the overall reliability of the structural system. This is further discussed in Section 5.2 below. (b) When managing the reliability by means of inspections, dependence signifies that an inspection of one element provides information on the deterioration at other elements as well (Straub and Faber 2005b). This is illustrated in Figure 8 and discussed in Section 6.

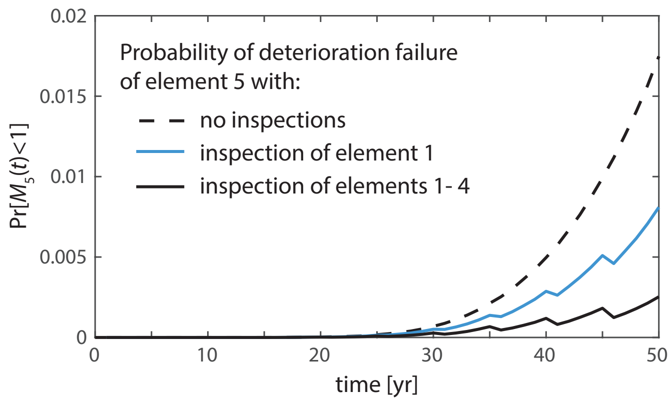

Figure 8: Probability of deterioration failure of element 5 in the example structure. The a-priori probability of failure is compared to (a) the case where inspection results from element 1 are available and (b) the case where inspection results are available from elements 1–4. In both cases, inspections are performed in 5 year intervals and it is assumed that all inspections reveal intact elements. The inspection is modeled following Section 6.1. This illustrates the effect of information obtained from correlated elements on the reliability of an un-inspected element.

5.1 *Modeling dependence*

Probabilistic deterioration models are developed mainly at the structural element level, resulting in a prediction of deterioration $D_i(t)$ at element i. Stochastic dependence can then be modeled by introducing a correlation among the $D_i(t)$s, or among the parameters of the models describing $D_i(t)$, such as B_i in the example of Section 2.1. The two most common classes of models to describe these correlations are *hierarchical models* and *random field models*.

Because a (if not the) main source for dependence are common influencing factors, a hierarchical model is a natural model for representing stochastic dependence. It is based on defining the deterioration $D_i(t)$ or its parameters by means of conditional probability distributions, which are conditioned on hyperparameters α that are common to a group of elements (Maes et al. 2008). These hyperparameters can be physical parameters (e.g. common environmental factors), joint model uncertainties or simply empirically determined parameters. It is also possible to introduce multiple hierarchies, as in the model of Figure 9 from Luque et al. (2017). There are a large number of applications of the hierarchical model described in the literature (e.g. Maes 2002, Straub et al. 2009, Qin and Faber 2012).

The hierarchical model has computational advantages. In particular, for fixed values of the hyperparameters, the $D_i(t)$s are conditionally independent, which can facilitate computation. For this reason, the model can also be employed purely for computational reasons. In particular, the case of equicorrelation among the $D_i(t)$s can be readily represented by a hierarchical model with a single hyperparameter α (Song and Kang 2009, Straub 2018). This has been exploited when modeling deteriorating structures through Bayesian networks (e.g., Schnei-

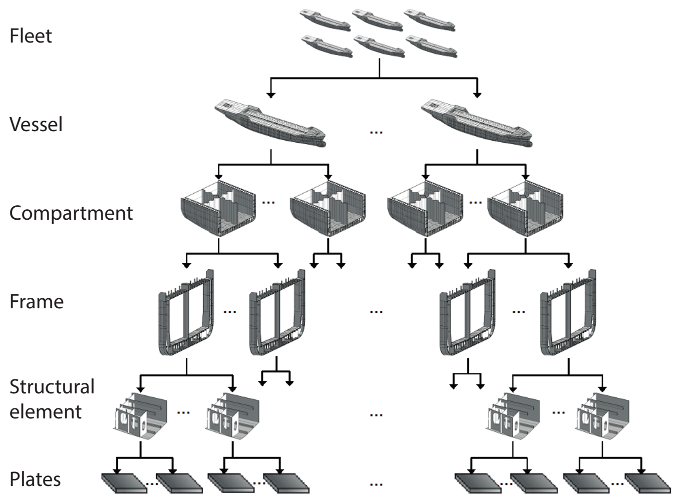

Figure 9: Hierarchical model for corrosion in ship structures. At each level of the hierarchy, common factors are introduced to represent the dependence among elements belonging to the same instance. At the lowest level (e.g. plates in a compartment), the model allows for a random field. The model is learned from thickness measurements in (Luque et al. 2017).

der et al. 2015, Luque and Straub 2016). For example, the equi-correlation among the deterioration parameters B_i of the example structure can be modeled by defining the B_is through conditional distributions (see Chapter 9 of Straub 2018):

$$F_{B_i|U_c}(b|u_c) = \Phi\left[\frac{F_{B_i}^{-1}(b) - u_c\sqrt{\rho}}{\sqrt{1-\rho_{U_c}}}\right] \quad (24)$$

wherein U_c is the hyperparameter with standard normal distribution, $F_{B_i}^{-1}$ is the inverse CDF of B_i and ρ_{U_c} is the equivalent correlation coefficient among the normal-transformed B_i as used in the Nataf transformation (Der Kiureghian and Liu 1986). (In the example of Section 2.1, $\rho_B = 0.6$ translates to $\rho_{U_c} = 0.626$.)

For continuously spatially distributed deterioration, e.g. corrosion on a surface, random field models are utilized (Hergenröder and Rackwitz 1992, Ying and Vrouwenvelder 2007, Stewart and Mullard 2007). The main parameter of these models, besides the marginal distributions, is the correlation length. Unfortunately, only few studies exist that measure correlation lengths for relevant parameters in real structures (e.g., Malioka et al. 2006).

For computational purposes, random fields must be discretized (e.g. Li and Der Kiureghian 1993, Betz et al. 2014). The resulting models have a significant number of input random variables, but this can be handled by state of the art reliability methods (e.g., Papaioannou et al. 2015, Allaix and Carbone 2016). A bigger challenge is the difficulty of lay engineers to understand the concept of random fields and their implications. One reason for this is the notorious difficulty in graphically representing 2D or 3D random fields, because a single plot can only show marginal information (e.g. a map of the mean or standard deviation) or one realization of the random field. While it is possible to show multiple realizations jointly, this is often confusing to non-experts. Good solutions for representing spatially dependent random variables are still sought.

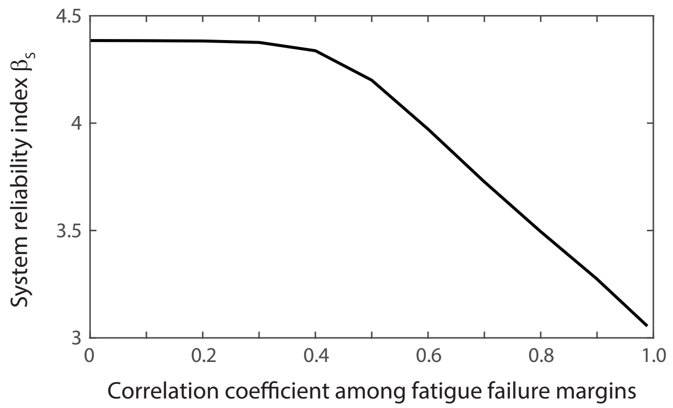

Figure 10: Reliability of a frame structure whose elements are subject to fatigue deterioration. The system reliability depends strongly on the correlation among fatigue failures in the elements (from Straub and Der Kiureghian 2011).

While dependence caused by common factors (represented by hierarchical models) should generally be included in the assessment, spatial variability as modeled by random fields can in some cases be represented by an equivalent random variable. However, explicit consideration of random fields is necessary if measurements are taken, in which case the correlation between the measured locations cannot be ignored (see Section 6). The random field must furthermore be included in the analysis when the dependence has a pronounced effect on the reliability, as discussed in the next section.

5.2 *Effect of dependence on the reliability of the structure*

In redundant systems, dependence among components can (severely) reduce the system reliability (Grigoriu and Turkstra 1979, Gollwitzer and Rackwitz 1990). Since most structural systems exhibit at least some redundancy, neglecting dependency can lead to a strong underestimation of the risk, as illustrated in Figure 10. This has been recognized, but including the dependence in the assessment has been hindered by the limited availability of models and data on dependence of deterioration in the structure.

Without inspection results, spatially varying deterioration is often modeled by means of a homogeneous random field (i.e. the marginal statistics are the same throughout the domain). In this case, a conservative approximation for reliability analysis is to consider the deterioration as identical throughout the domain (i.e. model it by means of a single random variable) with the marginal distribution of the random field. In many instances, this gives sufficiently accurate results. If a more accurate description is necessary, it might be possible to find an equivalent distribution of the representative random variable that leads to the same probability of failure estimate as a complete reliability analysis with the random field. This approach is applied in geotechnics (e.g., Griffiths et al. 2009). Finding similar approximations for non-homogenous random fields is challenging (Papaioannou and Straub 2017). It therefore remains to be investigated how to handle spatial variability in simplified reliability assessments when inspection and measurement data are available.

6 MAINTENANCE, INSPECTION AND MONITORING

Maintenance, inspection and monitoring are an essential part of the management of deteriorating structures. Maintenance regimes for technical systems can be classified as in Figure 11. For structural systems, which are almost always safety critical, corrective maintenance is not typically an alternative. However, for many structures, in particular smaller structures, it is common to adopt a do-nothing policy and act only upon the indication of a damage (which predominantly is not a failure but an indication of a damage). Such an approach can be interpreted as an ad-hoc condition-based maintenance strategy.

In contrast, professional owners and operators of infrastructure mostly have a systematic or condition-based maintenance policy, whereby maintenance and repairs are performed at regular intervals, combined with inspections. Upon indication of a potentially critical damage or deterioration process, a predictive approach is typically implemented, in which structural and deterioration models are utilized to predict the development of the damage. These predictions are ideally made with probabilistic models. In most cases, inputs to these models are provided based on tests and inspections on the structure.

As discussed earlier, deterioration models are often subject to large uncertainty. Hence a commonly adopted strategy is to combine predictive models with an inspection and monitoring plan. In a probabilistic setting, the data from inspection and monitoring can be directly included in the prediction using a Bayesian analysis, as outlined in the following subsection.

6.1 *The effect of inspection and monitoring on the reliability*

Arguably the most common approach to dealing with structures for which a potential deterioration problem has been identified is to perform inspections, possibly combined with monitoring. The effect of inspection on the reliability can be quantified consistently with Bayesian analysis (Tang 1973, Madsen 1987, Sindel and Rackwitz 1998, Faber 2000). Recent developments in Bayesian computation make the application to structural reliability problems rather straightforward from a computational point of view (e.g., Jensen et al. 2013, Straub and Papaioannou 2015). However, the application of the method in practice is still limited. Besides the general aversion of many engineers to probabilistic methods, there are a number of additional challenges. One is modeling the quality of the inspection data, i.e. the likelihood function describing the measurement data. Difficulties here involve the understanding of dependence among measurement results (Simoen et al. 2013, Goulet and Smith 2013), as well as the need for a model that connects the measurements with the quantity of interest. For example, a crack in a concrete structure can be an indication of a damage, but a model connecting this observation to the structural parameters is not necessarily available.

Another challenge in Bayesian updating is the need for a prior model. Because often no or only crude deterioration models are available, engineers are reluctant to employ a prior model. However, if the inspection is at all informative, then the inspection data will eventually dominate the reliability if weakly informative priors are used. This is illustrated in the following numerical example.

Consider the example structure. To reduce the probability of failure, it is decided to perform regular inspections at a 5 year interval. If a critical degree of damage is identified at the inspection, repair action would be initiated. The identification of a critical damage can be mathematically described by a probability of detection (PoD) function. For this application, the PoD is

$$PoD(D_i) = \Phi\left(\frac{0.5 - D_i}{0.2}\right) \tag{25}$$

At an inspection, all elements are checked. It is here assumed that all inspections (i.e. at all elements at all times) result in no-detection of a critical damage.

The conditional probability of failure given the inspection results can be computed with Bayesian updating. Here, the BUS approach is utilized to perform this updating (Straub and Papaioannou 2015, Straub et al. 2016). Figure 12 shows the resulting conditional probabilities of failure. Results are computed for the original model of Section 2.1 and the same structure with a modified deterioration model, mimicking a situation in which there is large uncertainty on the deterioration model.

The results of Figure 12 nicely show that the effect of the prior model is only limited and the updated reliability is ultimately dominated by the inspection results. The reliability of the (pessimistic) alternative model is initially low because of the large uncertainty associated with the deterioration process. However, the inspections, which reduce the uncertainty, ensure a minimum reliability that is quite constant throughout the service life. With increasing number of inspections the predicted reliability approaches that of the original, more informative model. For that model, the initial inspections have no effect because deterioration is not expected to have an effect before year 20 anyway.

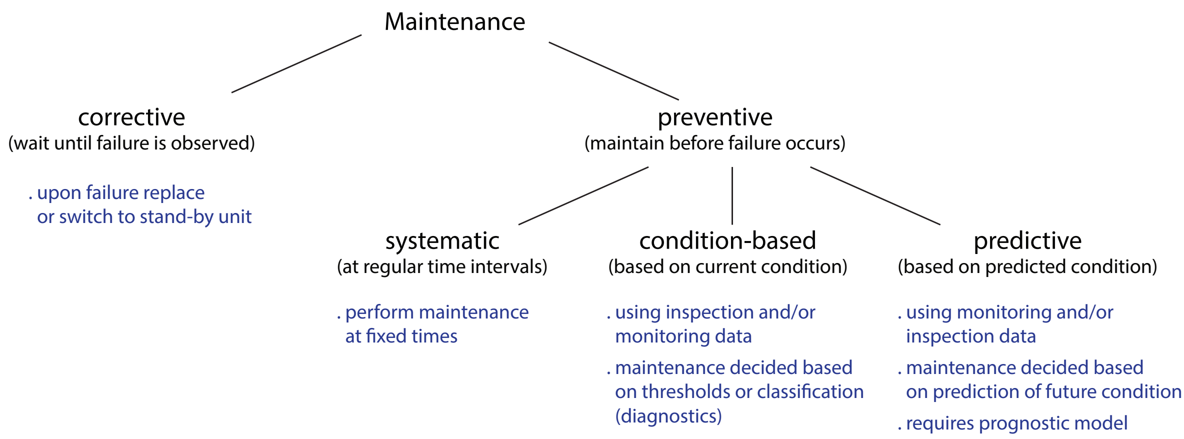

Figure 11: Summary of maintenance regimes (from Straub 2018).

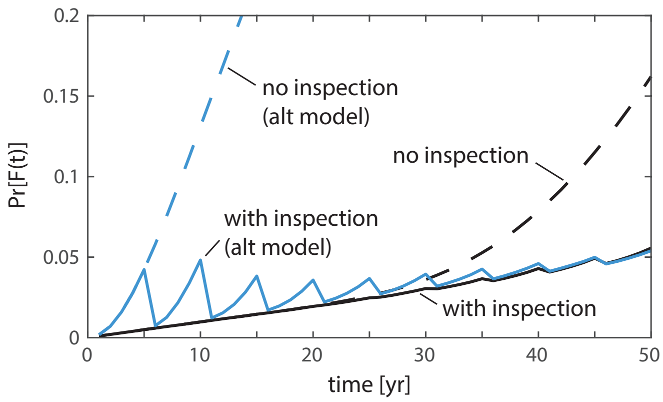

Figure 12: Probability of failure of the example structure, with and without inspections. Results are computed for the original model and an alternative model with increased uncertainty in the deterioration model. This alternative model corresponds to the original model with a modified standard deviation of B_i of 200 instead of 50.

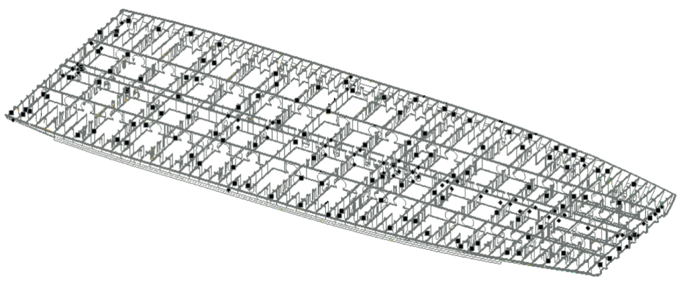

Figure 13: Locations (black dots) of thickness measurements in an inspection campaign on a ship structure (from Luque et al 2017).

6.2 *Spatially distributed inspection data*

Inspection and monitoring data is typically available at varying spatial locations. Exemplary, Figure 13 shows measurement locations in a ship structure. In some structures, data is available in a spatially distributed form, e.g. for reinforcement corrosion in concrete structures where continuous measurements of cover depth or half-cell potentials are made (Gehlen and von Greve-Dierfeld 2010).

Bayesian updating of structural reliability with spatially distributed inspection data has been considered for some time (Hergenröder and Rackwitz 1992). By modeling the correlation among deterioration at different locations, the effect of inspecting one component on the condition estimate at other locations can be computed, as illustrated in Figure 8. This effect is well acknowledged by engineers, who make an assessment of the entire structure by samples taken at selected locations only, thus implying such a correlation. However, it is still rarely evaluated quantitatively.

The large number of parameters arising from the random field discretization combined with the large amount of data arising from spatially distributed measurement leads to computational challenges that still have not been solved satisfactorily at the fundamental level. However, for most practical purposes, solutions can be found. In some cases, analytical solutions are available, notably for lognormal random fields (Straub 2011). In other cases, partial solutions can be found by using some of the data only to update the marginal distributions, but not the joint distribution of the random field. This is e.g. employed for obtaining the spatially distributed estimate of corrosion shown in Figure 14 (Straub et al. 2018).

As discussed in Section 5.2 above, an exact representation of the spatial random field may not be necessary for the reliability analysis, and the posterior random field may be reduced to a single random variable. However, for the purpose of assessing the durability and planning maintenance actions, a spatially explicit representation, such as shown in Figure 14, can be of great value.

6.3 *Planning and optimization of inspection and monitoring actions*

For many structures, inspections contribute significantly to the total life-cycle cost. Hence there is an interest in optimizing inspection efforts, by finding the optimal trade-off between the cost of inspections and the risk of failure (Figure 16). The effect of the inspection lies in the reduction of uncertainty in the structural condition. This in turn enables an improved (condition-based or predictive) planning of repair and

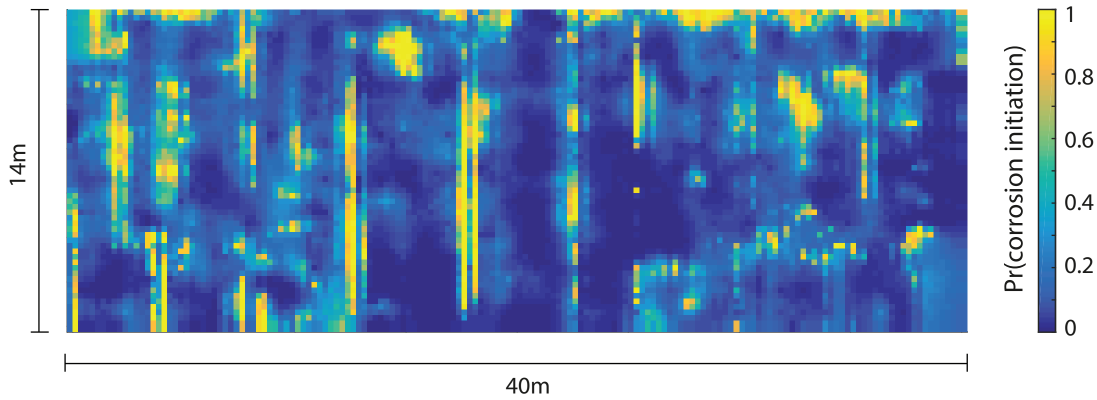

Figure 14: Probability of corrosion initiation (depassivation) in the reinforcement of a RC parking deck. Probabilities are evaluated by Bayesian updating of the corrosion model with spatially distributed inspection data from half-cell potential measurements, cover depth measurements and chloride profiles. From (Straub et al. 2018), based on data from (Gehlen and von Greve-Dierfeld 2010).

maintenance actions.

In fact, reliability- or risk-based inspection (RBI) planning has been one of the successful applications of structural reliability assessment in practice. Following the Alexander J Kieland disaster in 1980 (Almar-Naess et al. 1984), RBI planning has been developed and implemented for offshore structures subject to fatigue (Skjong 1985, Thoft-Christensen and Sorensen 1987, Madsen et al. 1990, Goyet et al. 1994, Faber et al. 2005). In RBI planning, Bayesian updating is utilized to quantify the effect of inspections on the uncertainty in the structural condition and on the reliability estimate (see Figures 8 and 12).

RBI planning is a special case of a sequential decision problem under uncertainty (Raïffa and Schlaifer 1961, Kochenderfer 2015). When planning an inspection for the next time step, the entire past history as well as all potential future decisions and outcomes must be considered. The corresponding decision tree is as shown in Figure 15. To facilitate practical solutions, RBI planning was mostly based on a heuristic solution to the sequential decision planning, whereby inspections are planned following simple criteria. For example, an element is inspected whenever its probability of failure exceeds a threshold. This threshold is then optimized to find the balance between risk and cost, as in Figure 16.

A challenge remains in the optimization of inspection efforts at the system level, which has been addressed explicitly only by a few publications (Straub and Faber 2005b, Papakonstantinou and Shinozuka 2014, Memarzadeh and Pozzi 2016). In (Luque and Straub 2018, Bismut and Straub 2018, Schneider et al. 2018) we propose an efficient framework based on a direct policy search, in analogy to the heuristic approach applied in practice for optimizing inspections at the structural element level.

Optimization of monitoring systems is conceptually simpler, as it is only necessary to compare the expected lifetime cost with or without the monitoring system. This difference corresponds to the value of information (VOI) of the monitoring system (Pozzi and Der Kiureghian 2011, Straub 2014, Thöns et al. 2015). However, the task also requires to quantitatively (probabilistically) predict future monitoring data, as well as the diagnostics based on these data. For most monitoring systems, which provide data on multiple parameters with high frequency, such models are not (yet) available. In the meantime, pragmatic approaches to appraise the VOI based on a mixture of expert judgment and simple models can be utilized (e.g. Zonta et al. 2014).

7 DISCUSSION

Assessment of deteriorating and existing structures is commonly seen as a major application area for structural reliability methods (Faber 2000, Ellingwood 2005). However, around 40 years after modern structural reliability analysis was invented, the number of reported practical applications of the theory to the assessment of deteriorating structures is still limited. In many countries, the assessment of deteriorating structures is mostly based on simplified and conservative engineering considerations. Among the applications that have been reported, most deal with the reliability of bridge structures (e.g. Faber et al. 2003, Strauss et al. 2009, Maljaars and Vrouwenvelder 2014). In addition, as reported in Section 6, reliability methods have to some degree found their place in the planning and optimization of inspections, where deterministic methods have difficulty in making any kind of quantitative statements.

It can be argued that the main role of reliability analysis is to serve as the basis for modern codes and standards. However, crucial aspects for the assessments of deteriorating and existing structures are not well developed in structural codes. As Ellingwood (2005) puts it, ”current codes of practice provide little guidance for the proper evaluation of existing facilities for continued service, since their focus is on new construction.” One major issue is that the simplified treatise of structural systems in semi-probabilistic code formats is not suitable for assessing existing structures (Ghosn et al. 2016). It does not

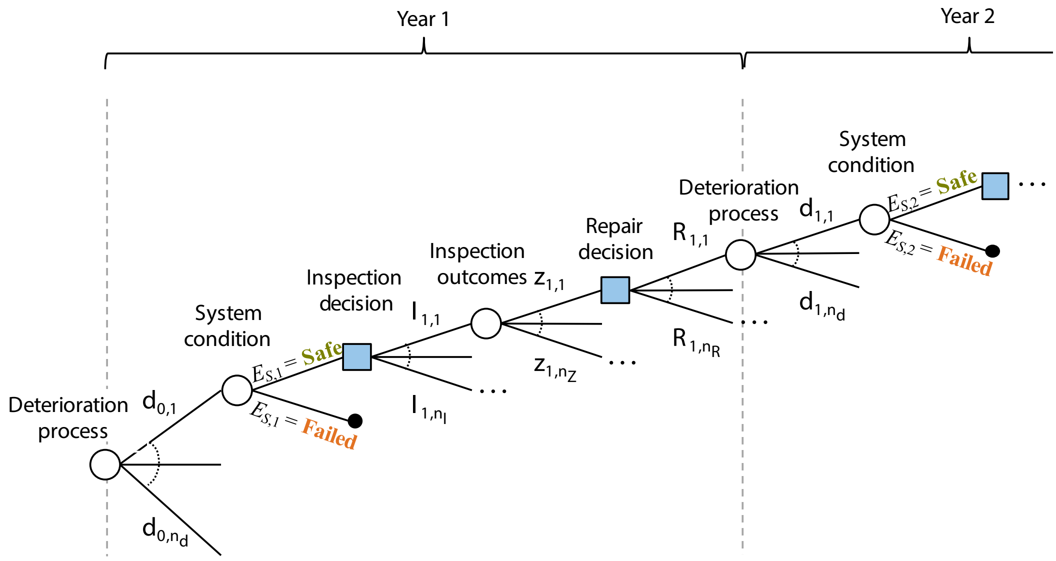

Figure 15: Schematic decision tree for risk-based inspection planning (from Bismut and Straub 2018).

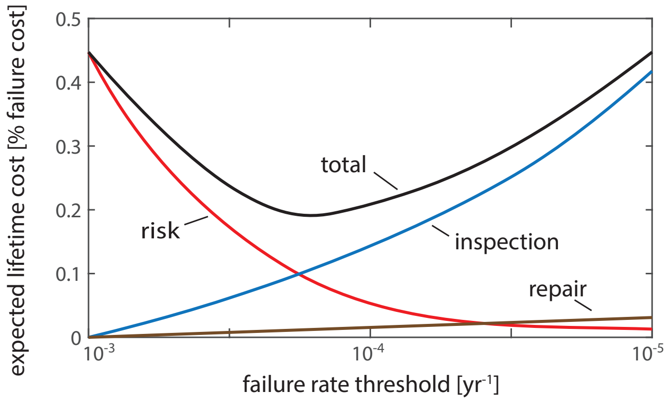

Figure 16: Expected lifetime cost in function of the threshold on the failure rate. Inspections are planned just before the failure rate estimate exceeds the threshold (after Straub and Faber 2005).

enable a proper understanding of the effect of deterioration on the structural reliability, as discussed in Section 4. Furthermore, with the exception of fatigue, in many design codes deterioration is not considered by means of explicit limit state functions. Rather, Eurocode requires structures to be in an as-new condition over its entire lifetime, which is reasonable for most new designs, but is of little help when deterioration is already present.

Current efforts to develop specific codes and standards for existing structures are a step in the right direction (Lüchinger et al. 2015). These standards will be more closely linked to structural reliability methods than the design standards, they can include the effect of deterioration on the reliability and they should aim at better addressing the need for more realistic system modeling. However, as discussed in Section 4, it is not actually straightforward to do so in a codified format, and future research should address this question. Standards for existing structures will also be closer aligned with a risk-based philosophy, thus enabling a more optimal management of deteriorating structures.

A main reason for the small role of reliability-based methods in the assessment of deteriorating structures lies in the fact that serviceability criteria often determine the need for intervention. This commonly involves bringing the structure back to a state without deterioration, and there is no need for a detailed assessment of the effect of deterioration on the system reliability. Another reason is that many structures become obsolete before deterioration plays a major role.

Many engineers argue that current practice is doing just fine without an increased utilization of structural reliability analysis. In recent times, there have been only a limited number of failures of structures caused by deterioration. Current practice has evolved over a long time period, and any aggregation of structural failures has triggered investigations and eventually an adjustment of the design and assessment rules. That evolution has ensured that structures today are reliable.

While one can state with some degree of certainty that current practice for designing and managing structures for durability does indeed lead to acceptable reliability, it is unclear to what degree it is optimal. Investigations into the optimality of possibly conservative models and assessment procedures are lacking. It is challenging to quantitatively investigate the degree of conservatism contained in current standards (Teichgräber et al. 2018). But there is a need for research in this direction, since regulating bodies and standardization bodies will not support changes towards more efficient assessment procedures without thoroughly understanding their effect on the safety of structures.

The good news is that the principles of structural system reliability and risk-based decision making are indeed applied in engineering design and management on a daily basis. For example, designers will automatically direct more attention to critical elements of a structure or rules for inspection planing distinguish between primary, secondary and tertiary members. Yet all this is limited to what is intuitively understood by the engineers. In more complex situations, the intuition of the engineer can fail and as a result possibly over-conservative solutions are implemented. I have witnessed multiple instances of structural rehabilitation projects where a proper stochastic modeling and reliability analysis might have saved substantial financial resources, but where these were not applied due to the lack of understanding or acceptance of these methods. In most, if not all, of these examples, a relatively simple model would have sufficed to assess whether or not a structure is sufficiently safe. However, to find the right simple model is challenging and requires insights into the topics discussed in this article. Up to now, the structural reliability community has not been very successful in bringing these messages across and increased efforts are needed to achieve this.

8 CONCLUSIONS

Structural reliability assessment provides a solid foundation for optimal management of deteriorating structures. However, there is still a long way ahead until reliability-informed planning and assessment becomes the norm rather than the exception. Research efforts are needed in particular on an improved modeling of system reliability that is compatible with standard structural assessment approaches, and on the understanding of the real reliability associated with current conservative modeling assumptions. Opportunities arise from improved IT, sensor and communication technology, which should be embraced to enhance our models. Most of all, we need to work on changing the current prescriptive approach to management and assessment of structures, in order to provide incentives to the structural engineering community for more realistic and optimal predictions in lieu of conservative assumptions.

9 ACKNOWLEDGMENTS

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