INFORMATION UPDATING IN ENGINEERING RISK ANALYSIS: OPPORTUNITIES, CHALLENGES AND RECENT DEVELOPMENTS

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ABSTRACT

Information (Bayesian) updating enables the combination of probabilistic models of engineering systems with observations made in-service, e.g. through monitoring, inspections, measurements or simple observations of system performance. The paper presents a short overview on recent developments in information updating for engineering risk analysis. Focus is put on computational aspects; in particular, novel modelling techniques and algorithms that improve the efficiency and/or the robustness of these computations are reviewed. The methods are illustrated with a number of examples, including a geotechnical site with deformation monitoring, inspections on deteriorating structures and near-real time risk assessment of infrastructure systems. The paper concludes with an outlook on the application of the methodology in practice and associated challenges in the modelling and the management of information.

1. INTRODUCTION

In most applications of risk and reliability analysis for structures and other large-scale engineering systems, probabilistic models are based on limited amount of representative data. This is true in particular for random variables describing model (epistemic) uncertainties, which are expensive to assess in experimental setups. As a consequence, epistemic uncertainty is often dominating the overall uncertainty in models of engineering systems. A commonly applied strategy to reduce this uncertainty is the collection of information during the service life of the system through inspections, monitoring or simple observations of system performance.

Information updating, also called Bayesian updating, enables the quantitative assessment of the uncertainty (and hence the risk) conditional on such information. It represents a consistent and powerful way to combine a-priori models with information gathered in-service. It also facilitates the quantitative analysis of the information content of different sources of information and thus provides a framework for optimizing the collection of information (e.g. the design of monitoring systems or the planning of inspection schedules).

Although information updating has been proposed since the 1970s (e.g. Tang 1973, Yang and Trapp 1974, Madsen 1987), it has been rarely applied in engineering practice and research until recently. A main reason for the reluctance of the industry to adopt this approach lies in the computational difficulties associated with performing information updating in practice (see also Straub and Faber 2006). For this reason, the author has been working on several strategies to facilitate such computations. This paper presents an overview on some of these developments and closes with an outlook on future research needs.

2. INFORMATION UPDATING

Let $\mathbf{X} = [X_1, \dots, X_n]^\mathrm{T}$ be a vector of basic random variables describing the considered engineering system, with joint probability density function $f(\mathbf{x})$. For the purpose of risk and reliability analysis, we are interested in the probability of one or more adverse events, commonly denoted by F (for failure). F can be represented by a domain Ω_F in the outcome space of $\mathbf{X}$. Often, the domain is defined through a (continuously differentiable) limit state function g such that

$$\Omega_F = \{g(\mathbf{x}) \leq 0\} \tag{1}$$

The corresponding probability is obtained from

$$\int_{\mathbf{x}\in\Omega_F} f(\mathbf{x})\mathrm{d}\mathbf{x} \tag{2}$$

This integration can be performed by well-known structural reliability methods, which include FORM, SORM and various simulation methods (e.g. Rackwitz 2001, Der Kiureghian 2005).

In analogy to the failure event, it is possible to model observation (information) events Z through domains Ω_Z in the outcome space of $\mathbf{X}$, by means of limit state functions $h(\mathbf{x})$. The information event Z is said to be of the inequality type if it can be written as

$$\Omega_Z = \{h(\mathbf{x}) \leq 0\} \tag{3}$$

and it is said to be of the equality type if it can be written as

$$\Omega_Z = \{h(\mathbf{x}) = 0\} \tag{4}$$

The situation is illustrated in Figure 1, with the failure domain Ω_F corresponding to the area $g(\mathbf{x}) \leq 0$ and the domain Ω_Z to the area $h(\mathbf{x}) \leq 0$ in the case of inequality information, and to the surface $h(\mathbf{x}) = 0$ in the case of equality information.

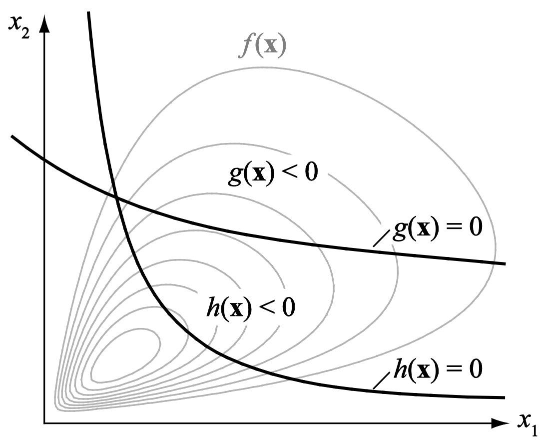

Figure 1. Illustration of the limit state surfaces and corresponding domains in information updating.

Our aim is to update the probability of F with the information Z, i.e. to compute the conditional probability of F given Z:

$$\Pr(F|Z) = \frac{\Pr(F \cap Z)}{\Pr(Z)} \tag{5}$$

This definition is based on the fact that the observed event Z reduces the outcome space to the domain Ω_Z.

The updated probability of failure can be computed in accordance with Eq. (2) as

$$\Pr(F|Z) = \frac{\int_{\mathbf{x}\in\{\Omega_F \cap \Omega_Z\}} f(\mathbf{x})\mathrm{d}\mathbf{x}}{\int_{\mathbf{x}\in\Omega_Z} f(\mathbf{x})\mathrm{d}\mathbf{x}} \tag{6}$$

The nominator corresponds to an integration of $f(\mathbf{x})$ over the domain Ω_F in the reduced outcome space Ω_Z. The denominator is merely a normalization constant that takes care of the fact that the outcome space has been reduced to Ω_Z.

In practice, there are several challenges involved in the computation of Eq. (6). A main issue is the fact that direct application of Eq. (6) is not possible if information is of the equality type. In that case, it is $\Pr(Z) = 0$ and both the denominator and the nominator result in zero. In the past, surface integration (Schall et al 1988) or evaluation through the computation of derivatives (Madsen 1987) were applied to circumvent the problem. However, in practice those approaches were limited to first- and second-order approximations, which do not always perform well. Recently, the author has proposed a different approach that proceeds by transforming the equality into inequality information and thus enables the use of all structural reliability method (Straub 2010). The approach is summarized in Section 3.

Several other challenges in the computation of Eq. (6) remain. For one, the limit state functions describing the domains can be complex (they are often described by FE models) and computationally expensive; the number of evaluations of the limit state functions might thus be limited. Furthermore, the probability of both the nominator and denominator reduces with increasing amount of information. This limits the use of crude simulation techniques. On the other hand, FORM, SORM and some advanced simulation methods require optimization for finding the so-called design point. This optimization is non-trivial and makes it difficult to include algorithms in software, which can perform information updating automatically without the interference of the user. For these reasons, research has been carried out on using so-called Bayesian networks (BNs) for information updating. Ongoing research on BNs for this application is briefly reviewed in section 4.

3. INFORMATION UPDATING WITH EQUALITY INFORMATION

We make use of the fact that the likelihood function provides an alternative to domains Ω_Z for modeling (uncertain) information. The likelihood function is commonly used in statistics and corresponds to the likelihood of the observation given the true system state $\mathbf{X} = \mathbf{x}$:

$$L(\mathbf{x}) \propto \Pr(Z|\mathbf{X} = \mathbf{x}) \tag{7}$$

As shown in Straub (2010), any domain Ω_Z can be translated into a likelihood function. However, in most cases it is more convenient to directly identify the likelihood function. As an example, consider a measurement s_m of a system characteristic $s(\mathbf{X})$. The measurement has an additive error ϵ that is a zero mean random variable uncorrelated with $\mathbf{X}$. The limit state function $h(\mathbf{x}, \epsilon)$ describing this equality information as well as the corresponding likelihood function are given in the following, with $f_\epsilon()$ being the PDF of ϵ.

$$h(\mathbf{x}, \epsilon) = s(\mathbf{x}) - s_m + \epsilon \tag{8}$$

$$L(\mathbf{x}) = f_\epsilon(s_m - s(\mathbf{x})) \tag{9}$$

For the case of several observation events $Z_i, i = 1, \dots, n$, the corresponding likelihood functions $L_i(\mathbf{x}), i = 1, \dots, n$ can always be combined into a single likelihood function $L(\mathbf{x})$. E.g., if measurements are uncorrelated for given $\mathbf{X} = \mathbf{x}$, it is simply $L(\mathbf{x}) = \prod_{i=1}^{m} L_i(\mathbf{x})$. Therefore, $L(\mathbf{x})$ is a general format for describing any information that can become available on the system.

In Straub (2010), it is shown that it is possible to define an equivalent information event Z_e based on the likelihood. This event is described by the following limit state function and associated domain:

$$h_e(\mathbf{x}, u) = u - \Phi^{-1}(cL(\mathbf{x})) \tag{10}$$

$$\Omega_{Z_e} = \{h_e(\mathbf{x}, u) \leq 0\} \tag{11}$$

wherein U is a standard Normal random variable, c is a constant that can be freely chosen to ensure that $cL(\mathbf{x}) \leq 1$ for any $\mathbf{x}$ and $\Phi^{-1}()$ is the inverse cumulative standard Normal distribution function. Note the correspondence of (10) to the nested reliability formulation proposed in Wen and Chen (1987).

It can then be shown (Straub 2010) that an alternative to Eq. (6) is available through the following identity

$$\Pr(F|Z) = \Pr(F|Z_e) = \frac{\int_{\mathbf{x} \in \{\Omega_F \cap \Omega_{Z_e}\}} f(\mathbf{x}) \mathrm{d}\mathbf{x}}{\int_{\mathbf{x} \in \Omega_{Z_e}} f(\mathbf{x}) \mathrm{d}\mathbf{x}} \tag{12}$$

The only difference between Eq. (6) and Eq. (12) lies in the use of the domain Ω_{Z_e} instead of Ω_Z. Since Ω_{Z_e} by definition (11) corresponds to a finite domain in the outcome space of $\mathbf{X}$, the corresponding integrations result in values larger than zero and the computation of Eq. (12), unlike Eq. (6), can be performed with any structural reliability method.

3.1 APPLICATIONS

The first application is taken from Straub (2010) and considers a classical fatigue crack growth problem taken from Ditlevsen and Madsen (1996). The crack depth in a structural component after n stress cycles with range ΔS is

$$a(n) = \left[\left(1 - \frac{m}{2}\right) C \Delta S^m \pi^{\frac{m}{2}} n + a_0^{\left(1 - \frac{m}{2}\right)}\right]^{\frac{1}{1 - \frac{m}{2}}} \tag{13}$$

Here, a_0 is the initial crack size, C and m are material parameters. The reliability of the component after n cycles is described by the following limit state function:

$$g(\mathbf{x}) = a_c - a(n) \tag{14}$$

where a_c is the critical crack size.

Measurements of the crack size at different points in time are considered, resulting in $a_{m,i}$. The likelihood function for a measurement after n_i cycles is

$$L_i(\mathbf{x}) = f_{\epsilon_i}(a_{m,i} - a(n_i)) \tag{15}$$

The joint probabilistic model of the random variables $X = [C, m, \Delta S, a_0, \epsilon_1, \epsilon_2]$ is given in Straub (2010). Here, we consider two measurements and compute the conditional probability of failure according to Eq. (12), whereby the integrals are evaluated using Monte Carlo simulation (MCS) with 10^6 samples. The results are shown in terms of the reliability index $\beta = \Phi^{-1}(\Pr(F|Z))$ in Figure 2.

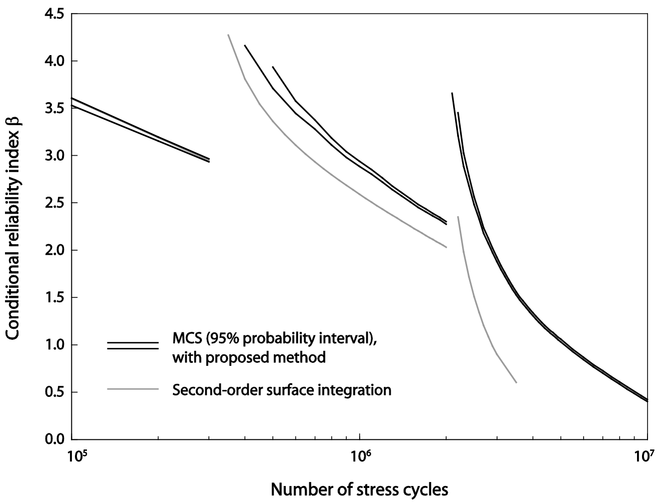

Figure 2. Results for the crack growth example.

As evident from the results shown in Figure 2, MCS gives sufficiently accurate results, which have the advantage of being unbiased. For comparison, the results obtained with a second order surface integration (Schall et al. 1988) are also shown, which strongly underestimate the true reliability index. For $n \geq 4 \cdot 10^6$, no results could be obtained with this approach, due to algorithmic difficulties in the design point search (this is not a fundamental problem and could be overcome by improving the applied optimization algorithm, but it is quite common in practical implementations of the second-order surface integration approach).

The second application is taken from Papaioannou and Straub (2010) and considers information updating at a geotechnical construction site. It demonstrates that the information collected during the construction process can be utilized to update the reliability at the most critical stage.

Consider the geotechnical site sketched in Figure 3. It consists of an excavation supported with sheet pile walls. The excavation will reach a depth of 5m at the final stage. As is commonly done at geotechnical sites, a monitoring system is installed, which measures the horizontal deformation at the top of the sheet pile walls.

Failure of the system is defined as the horizontal deformation at the top of the excavation, $u_{x,5\mathrm{m}}$, exceeding 0.1m, with corresponding limit state function

$$g(\mathbf{x}) = 0.1m - u_{x,5\mathrm{m}}(\mathbf{x}) \quad (16)$$

where $u_{x,5\mathrm{m}}(\mathbf{x})$ is computed through a non-linear FEM code (a realization of the deformation at the final excavation step is shown in Figure 4). The random variables $\mathbf{X}$ represent discretized random fields of soil and material parameters (the total number of random variables is 432).

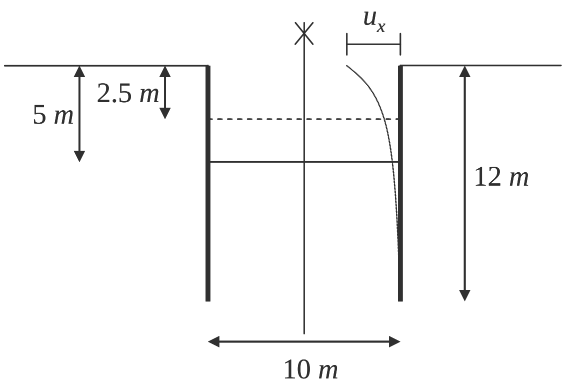

Figure 3. Situation of the geotechnical example.

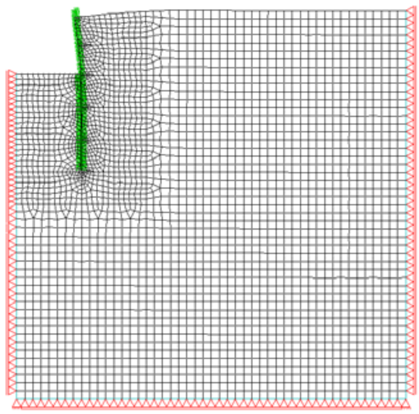

Figure 4. FEM output of the deformations at the final excavation step (not to scale), from Papaioannou and Straub (2010).

In the analysis, we consider a single measurement $u_{xm,2.5\mathrm{m}}$ made at the intermediate construction step when the excavation reaches 2.5m. The corresponding likelihood function is

$$L(\mathbf{x}) = f_\epsilon(u_{xm,2.5\mathrm{m}} - u_{x,2.5\mathrm{m}}(\mathbf{x})) \quad (17)$$

With the corresponding limit state function (10), the conditional probability of exceeding the critical deformation at the final step is computed according to Eq. (12). Due to the computationally demanding FEM model, an efficient method is required to evaluate the integrals in Eq. (12) for this application. The subset simulation method (Au and Beck 2001) is employed and found to be both robust and efficient (between 2000 and 4000 limit state function calls were required for the presented solutions).

The probability of failure is updated considering different measurement results $u_{xm,2.5\mathrm{m}}$. The results are summarized in Table 1.

Table 1. Results of the reliability of the excavation site conditional on different deformation measurement outcomes at the intermediate excavation step.

Measurement	$\Pr(F\|Z)$
No measurement	1.4×10^{-2}
$u_{xm,2.5\mathrm{m}} = 10\mathrm{mm}$	2.2×10^{-1}
$u_{xm,2.5\mathrm{m}} = 5\mathrm{mm}$	2.1×10^{-2}
$u_{xm,2.5\mathrm{m}} = 2\mathrm{mm}$	6.8×10^{-3}

To interpret the results, it is useful to compare the measured deformation $u_{xm,2.5\mathrm{m}}$ with the expected deformation according to the a-priori model, calculated as $\mathrm{E}\left[u_{x,2.5\mathrm{m}}(\mathbf{X})\right] = 2.6\mathrm{mm}$. When observing a deformation much larger than this value (e.g. 10mm), the probability of failure increases significantly. When observing a value close to this expected value (here 2mm), the probability of failure is significantly lower than the prior probability, due to the fact that an observation of a value close to the expected value reduces the uncertainty without increasing the mean estimate.

As seen from this example, simple measurements can contain significant amounts of information. The corresponding increase or decrease in reliability can be consistently quantified using information updating. With the proposed method, the implementation of information updating is straightforward using any of the available structural reliability methods, many of which are implemented in commercial software such as Strurel (Gollwitzer et al. 2006).

4. BAYESIAN NETWORKS FOR INFORMATION UPDATING

An alternative to using structural reliability methods for information updating are Bayesian networks (BNs). BNs have been developed during the past 25 years, mostly in the field of artificial intelligence, for representing probabilistic information and reasoning (Russell and Norvig, 2003). They have found applications in many fields such as statistical modeling, language processing, image recognition and machine learning. BNs have become increasingly popular for engineering risk analysis in recent years; applications in this field are reported, e.g., in (Friis-Hansen, 2000; Faber *et al.*, 2002; Friis-Hansen, 2004; Mahadevan and Rebba, 2005; Grêt-Regamey and Straub, 2006; Nishijima *et al.*, 2009; Bensi *et al.*, 2009).

There are a number of introductory texts to BNs available, e.g. Jensen and Nielsen (2007) or Langseth and Portinale (2007). In the following, it is assumed that the reader has a basic familiarity with BNs.

4.1 ENHANCED BAYESIAN NETWORK (EBN)

BNs are a powerful modelling framework when it is possible to exploit conditional independence among random variables. This is the case for most applications of engineering risk analysis, where the relation among random variables is often characterized by causal relations (A causes B). One example of such a dependence structure is given in Figure 5.

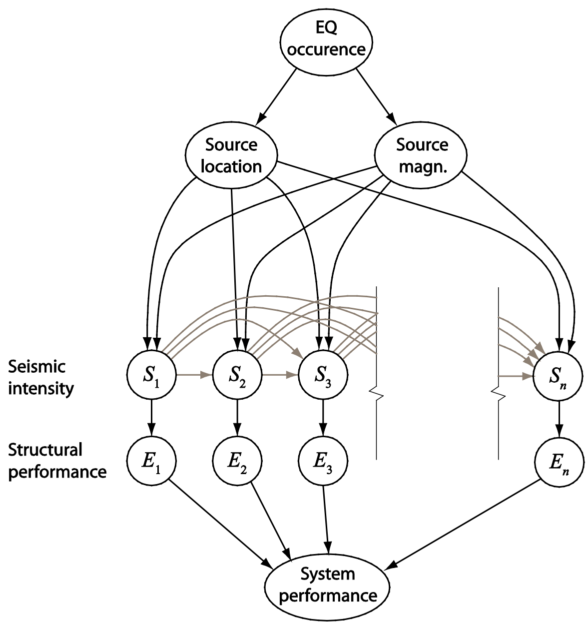

Figure 5. Conceptual BN model for spatial modeling of seismic hazard analysis of an infrastructure system (Straub et al. 2008).

In the example given in Figure 5 it can be observed that the spatial correlation between the seismic intensity at different locations leads to a large number of links. This is one example of a dependence that is not efficiently represented by a BN (although it is investigated if such dependence structure can be efficiently approximated within a BN as well, Straub et al 2008).

To be computationally efficient and robust, it is preferable that the random variables in the BN be discrete (i.e. they should be defined in a finite outcome space) and that the number of links to a single node be limited. This condition is often not found in applications of engineering risk analysis. To overcome this limitation of the BN, Straub and Der Kiureghian (2010a,b) propose an extension of the BN framework, termed enhanced Bayesian Network (eBN), by combining it with structural reliability methods.

The eBN proceeds by modelling the problem by a hybrid Bayesian network, which has both discrete and continuous random variables as nodes (e.g. Langseth et al. 2009). To perform inference in this hybrid BN, the eBN approach first eliminates all continuous nodes using a classical node elimination algorithm (Shachter 1986). This process is illustrated for one example in Figure 6, where the continuous random variable X is removed. It can be observed that the removal of X leads to new links, which make it necessary to compute the conditional probabilities $p(y_5|y_3, y_4)$ and $p(y_6|y_3, y_4, y_5)$. In the eBN approach, structural reliability methods are employed to compute these conditional probabilities.

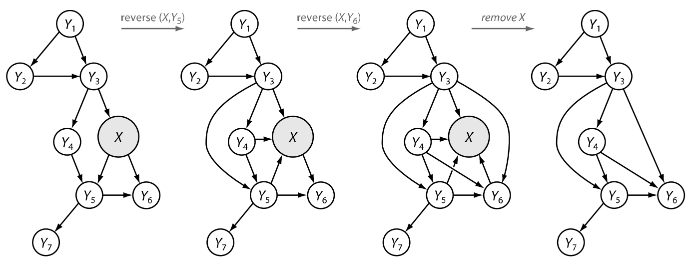

Figure 6. Illustration of an eBN and a link reversal sequence for removal of the continuous node X (from Straub and Der Kiureghian 2010a).

Once all continuous nodes are removed from the network, inference can be performed using the usual exact inference algorithms (e.g. the junction tree algorithm, Jensen and Nielsen 2007).

The eBN has its own limitations in regard to model complexity. When the network is too dense, computation may be either too time- or memory-consuming. However, when applying the eBN approach, a number of modeling techniques are available to ensure the computational efficiency of the approach, as described in Straub and Der Kiureghian (2010a,b). Not least, the eBN offers the possibility to quantify the computational efforts associated with a given model, which is a powerful ability in developing models of complex systems. In doing so, the eBN provides a formalism for analyzing any model that require structural reliability calculations (most of which are not commonly model by BNs).

One example from Straub and Der Kiureghian (2010b) is briefly summarized in the following. It demonstrates how the eBN enables the multiscale probabilistic modelling of complex infrastructure systems where various type of information is available. Due to the dependences among the system elements, this information propagates in the system. This is consistently quantified using the information updating facilities of the BN.

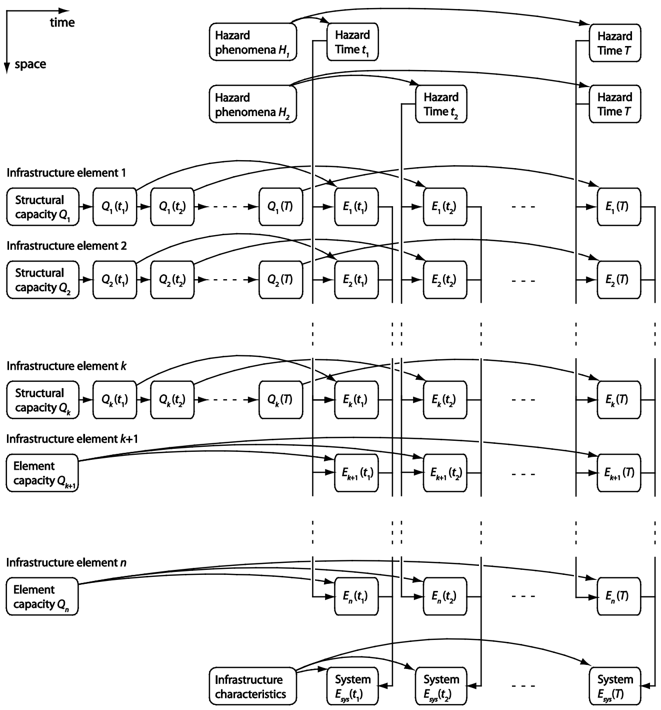

Figure 7. A spatial-temporal eBN model of an infrastructure system. Here, $E_i(t)$ is the performance of system component i at time t (Straub and Der Kiureghian 2010b).

Consider the eBN model shown in Figure 7. It models a transportation infrastructure system with components (these include structural systems such as bridges and non-structural components such as control elements). The system is subject to natural hazards (EQ, wind) and deterioration of system components.

The eBN shown in Figure 7 makes use of the object-oriented BN methodology. Each oval node corresponds to an object (an instantiation of the corresponding class). The classes that are used to construct the eBN of Figure 7 are shown in Figure 8. Each of the objects in the system model is an eBN with input and output nodes (the attributes of the class). As an example, the object *structure j* represents the time-invariant characteristics of bridge *j*. Or the object *deterioration* represents the condition of one bridge at a particular point in time (each bridge is at each time step represented by a new object *deterioration*).

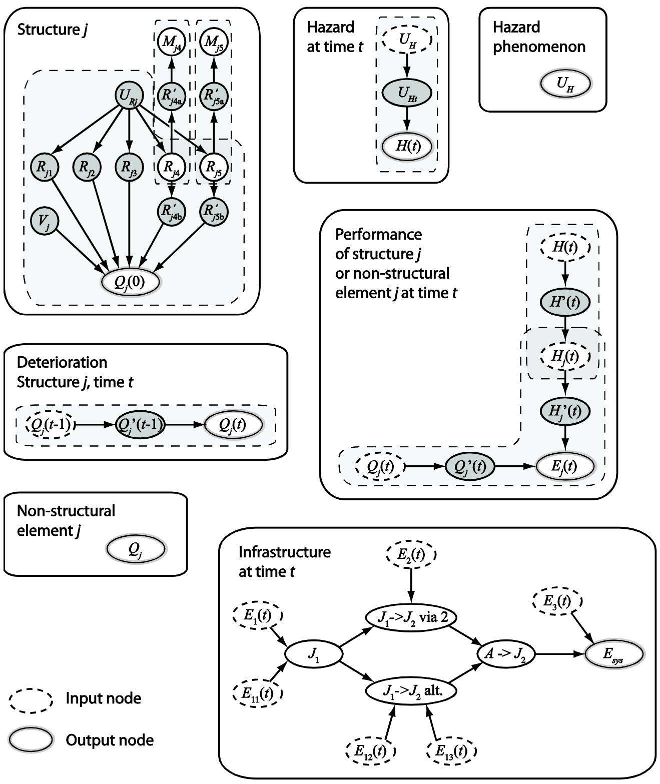

Figure 8. The classes/objects of the eBN for the example infrastructure, shown in Figure 7. The objects are connected through their input and output nodes.

With the object-oriented BN methodology, the fact that system elements are repetitive can be exploited. Therefore, the full system model can be assembled with little effort, while each system element (e.g. bridge) can be modelled to any desired level of detailing. Thus, the approach enables the multiscale application of information updating: Information obtained on any of system elements (or elements thereof) is consistently propagated through the entire model. As an example, it is possible to update the hazard model by observing the performance of structures. (Mostly it has been found that the information content of observations of structural performances with respect to the hazard model are low except for extreme observations, e.g. Straub et al (2008). However, the key issue is that the approach enables the quantification of this effect and also allows determining which information should be considered in the analysis).

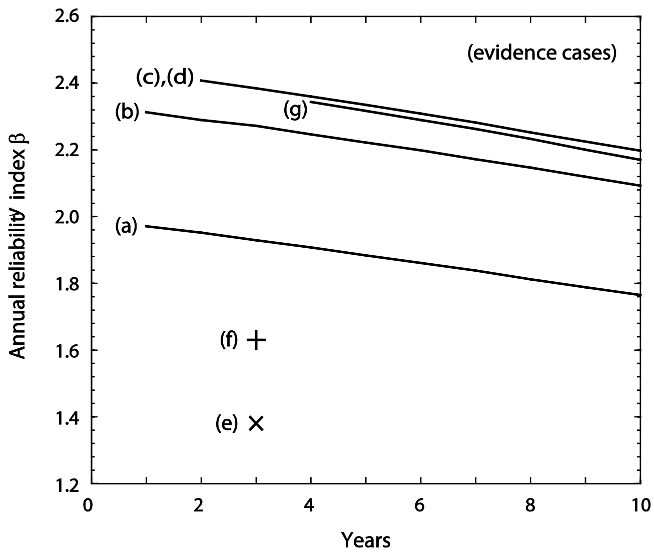

Figure 9. Reliability index of the infrastructure system conditional on the sequence of observations.

To demonstrate the potential of the eBN framework as a tool for information updating in the context of near-real-time infrastructure risk assessment, the model is applied to determine the reliability of the network as a function of time with information evolving in time. An exemplary sequence of observations is considered, with results summarized in Figure 9. The analysis starts with the a-priori case (a) that corresponds to the information available during the design phase. After construction of the infrastructure, measurements of the capacities of the structural elements are made, step (b). Thereafter, in the first two years of service, relatively low environmental loads are observed, together with the performance of the system elements, steps (c) and (d). In the third year, an extreme hazard event occurs. During the event, the only available information is that the hazard intensity is above a certain level, step (e). (For certain hazards, e.g., windstorms, predictions of H could also be included prior to the event.) Immediately after the event, the available information is still incomplete and only the performances of two system elements are known, step (f). Finally, in the aftermath of the hazard event, the performance of the entire system and the exact hazard intensity become known, step (g). Figure 9 summarizes the reliability updated with all available information up to the respective time step.

4.2 DYNAMIC BAYESIAN NETWORKS FOR INSPECTION AND MONITORING OF DETERIORATING STRUCTURES

Another example of the use of BN for information updating is provided in Straub (2009). There, a special class of BNs, namely dynamic Bayesian networks (DBNs), is applied as a framework for probabilistic modelling of deterioration processes and associated observations such as inspection or monitoring results. A generic DBN model that can represent all common deterioration models is proposed, as shown in Figure 10. (An earlier, less formal example of a BN application for deterioration modelling was presented by Friis-Hansen 2000).

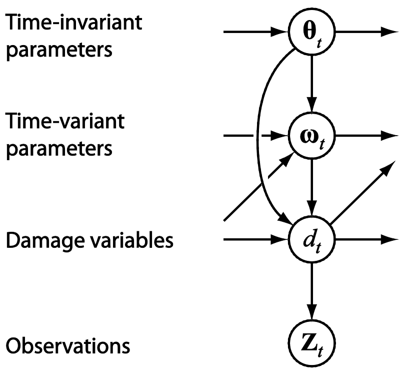

Figure 10. One time slice of the generic DBN deterioration modelling framework.

In the following, an application of the DBN framework is presented. For illustrative purposes, we consider the same fatigue crack growth example as described in Section 3.1. The DBN corresponding to this example is shown in Figure 11. Here, the random variable $q = C\Delta S^m$ is introduced to reduce computational efforts. The variables Z_t are the (potential) observations and the variables E_t model the condition of the structural element (survival/failure).

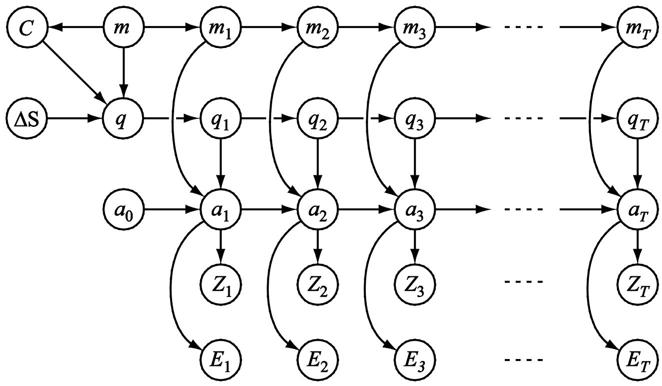

Figure 11. DBN implementation of the fatigue crack growth model from Section 3.1.

Results are given exemplarily in Figure 12 for the case of an inspection every 10^6 cycles, with no indication of a defect (no detection) at all inspections (for validation, the results of a Monte Carlo simulation with 10^6 samples are included).

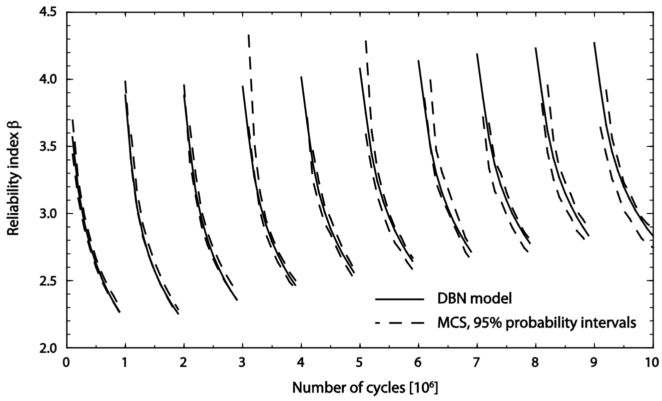

Figure 12. Results for the conditional case, with no indication of a defect at all inspections, (Straub 2009).

The main benefit of using the DBN for these calculations lies in the computational robustness and effectiveness. Once the DBN is established, the computation of the results presented here takes in the order of 10 CPU seconds on a standard PC with a 2.0 GHz processor with a Matlab-based program. The computation time increases linearly with the number of time steps considered (the 10 CPU seconds correspond to 100 time steps), but is independent of the number of observations.

Because the exact inference algorithm for the deterioration DBN model from Straub (2009) exclusively performs summations and multiplications, the algorithm is certain to work under any circumstance and can thus be implemented in software to be used by the engineer who has no detailed knowledge of structural reliability computations.

Besides providing the conditional reliability, the DBN can update the probability distribution of any of the random variables in the model without additional computational efforts. Exemplarily, Figure 13 shows the mean value of the crack depth conditional on measurements as a function of time. Here it is distinguished between *filtering*, which updates the probability distribution at time t conditional on all measurements up to time t, and *smoothing*, which updates the probability distribution at time t conditional on all measurements, including those made later than t.

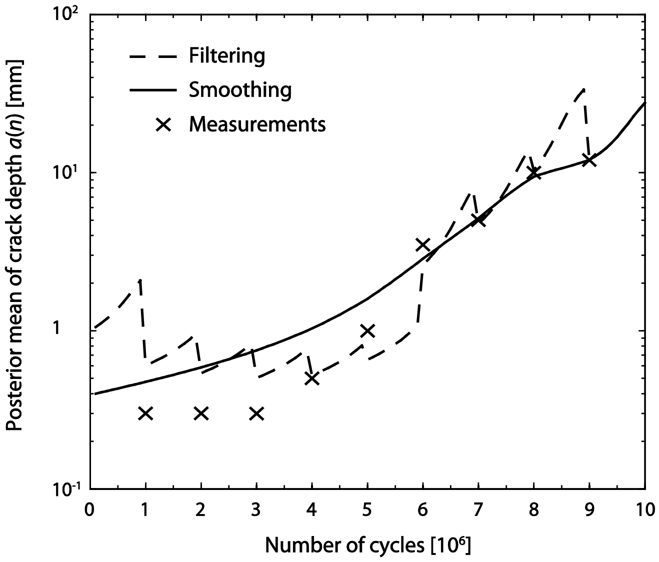

Figure 13. Posterior mean of the crack depth $a(n)$, updated with measurements of crack depths (Straub 2009).

5. OUTLOOK AND CONCLUSION

In most applications of engineering risk analysis, a significant or even dominant part of the uncertainty is epistemic. It can thus be significantly reduced by collecting relevant information. As reviewed in this paper, computational methods exist for efficiently updating the probabilistic model and the reliability estimate with information, thus quantifying the reduction in uncertainty. The vision of this author is that in the future any relevant information collected on critical systems will be automatically included in an information updating algorithm, to compute an updated system model at any time. This facilitates near-real-time decision making, where relevant decisions on risk mitigation actions are made continuously as information evolves. Applications are manifold, and include e.g. the monitoring and risk control in engineering systems subject to deterioration or the planning of emergency response during and after large natural hazards. Before this vision will materialize, however, a number of challenges must be tackled, some of which are briefly discussed in the following.

Arguably the largest challenge lies in the necessity for accurate models of the engineering system and the relevant processes (such as deterioration mechanisms). Highly simplified models, which are often sufficient for design purposes, are generally not suitable when considering information updating. One example is the correlation between random variables. For design purposes, this correlation can often be neglected (e.g. in series systems, this is a conservative approach). However, in information updating, the correlation must be estimated, since it will determine how much the uncertainty is reduced on the random variables that are not directly observed. (An example is a pipeline subject to inspections on 5% of its length. To determine the risk reduction from the inspection using information updating, correlation must be considered.) Similarly, it is necessary to represent the actual mechanisms acting in engineering systems as accurately as possible. As an example, the Palmgren-Miner model is normally sufficient for fatigue design but cannot be used for information updating, where a fracture-mechanics-based model is required instead.

Computational aspects were discussed in this paper. Here, a few challenges still remain, in particular for systems where large amount of data are collected in the spatial and temporal dimension (from continuous monitoring). To date, the methods presented in this paper work well with a limited number of information events only. Thus, when large amounts of data points are available, they cannot be directly considered for information updating, except when direct observations of individual model parameters are made. However, the data obtained from monitoring is generally highly correlated. Therefore, it can be promising to investigate strategies for reducing the data.

Finally, an important challenge for information updating lies in the way engineering systems are managed. Information updating requires the systematic collection and storage of data. Thanks to the advent of information technology, this has become greatly simplified and a number of industries have realized the importance of this task. However, in some fields, most notably the construction industry, there have been little efforts to collect data systematically in the past. In addition, even when data is collected and managed, it is not always the case that it is done so in the format required for information updating. It is up to engineers and risk analysts to convince decision makers in companies and regulatory bodies of the benefits of information updating.

Consider an ideal world where the author's vision of a systematic collection of information and associated updating of models of engineering systems is the norm. Once such a standard practice would be implemented, the principles of information updating could equally be used to continuously improve the models of engineering systems in general. In particular, this would provide the possibility to quantify model and other epistemic uncertainties, and a full probabilistic model of the (engineering) world might one day be available. Obviously, it is a long way to go until such an ideal situation is reached, but any intermediate step presents an opportunity in itself.

REFERENCES

Au S.K. & Beck, J.L. 2001. Estimation of small failure probabilities in high dimensions by subset simulation. *Probabilistic Engineering Mechanics* 16(4): 263-277.

Bensi M. T., D. Straub, P. Friis-Hansen, and A. Der Kiureghian (2009), Modeling infrastructure system performance using BN, in *Proc. ICOSSAR'09*, Osaka, Japan.

Der Kiureghian A. (2005), First- and second-order reliability methods. Chapter 14, in *Engineering design reliability handbook*, edited by E. Nikolaidis et al., CRC Press, Boca Raton, FL.

Ditlevsen O., and H. O. Madsen (1996), *Structural Reliability Methods*, John Wiley & Sons.

Faber M. H., I. B. Kroon, E. Kragh, D. Bayly, and P. Decosemaeker (2002), Risk Assessment of Decommissioning Options Using Bayesian Networks, *Journal of Offshore Mechanics and Arctic Engineering*, **124**(4), 231–238.

Friis-Hansen A. (2000), Bayesian Networks as a Decision Support Tool in Marine Applications, *PhD thesis*, DTU, Lyngby, Denmark.

Friis-Hansen P. (2004), Structuring of complex systems using Bayesian network., in *Proceedings Workshop on Reliability Analysis of Complex Systems*, Technical University of Denmark, Lyngby.

Gollwitzer S., B. Kirchgäßner, R. Fischer, and R. Rackwitz (2006), PERMAS-RA/STRUREL system of programs for probabilistic reliability analysis, *Structural Safety*, **28**(1-2), 108–129.

Grêt-Regamey A., and D. Straub (2006), Spatially explicit avalanche risk assessment linking Bayesian networks to a GIS, *Natural Hazards and Earth System Sciences*, **6**(6), 911–926.

Jensen F. V., and T. D. Nielsen (2007), *Bayesian Networks and Decision Graphs.* Information Science and Statistics, Springer, New York, NY.

Langseth H., and L. Portinale (2007), Bayesian networks in reliability, *Reliability Engineering & System Safety*, **92**(1), 92–108.

Langseth H., T. D. Nielsen, R. Rumí, and A. Salmerón (2009), Inference in hybrid Bayesian networks, *Reliability Engineering and System Safety*, **94**(10), 1499–1509.

Madsen H. O. (1987), Model Updating in Reliability Theory, in *Proc. ICASP 5*, Vancouver, Canada.

Mahadevan S., and R. Rebba (2005), Validation of reliability computational models using Bayes networks, *Reliability Engineering & System Safety*, **87**(2), 223–232.

Nishijima K., M. A. Maes, J. Goyet, and M. H. Faber (2009), Constrained optimization of component reliabilities in complex systems, *Structural Safety*, **31**(2), 168–178.

Papaioannou I., Straub D. (2010). Geotechnical reliability updating using stochastic FEM. *Reliability and Optimization of Structural Systems* (ed. D. Straub), Taylor and Francis.

Rackwitz R. (2001), Reliability analysis – a review and some perspectives, *Structural Safety*, **23**(4), 365–395.

Russell S. J., and P. Norvig (2003), *Artificial intelligence: a modern approach*, Prentice-Hall, Englewood Cliffs, N.J.

Schall G., S. Gollwitzer, and R. Rackwitz (1988), Integration of multinormal densities on surfaces, in *Proc. 2nd IFIP WG 7.5 Working Conference*, London.

Shachter R. D. (1986), Evaluating Influence Diagrams, *Operations Research*, **34**(6), 871–882.

Straub D., Der Kiureghian A. (2010a). Bayesian Network Enhanced with Structural Reliability Methods. Part A: Theory. *Journal of Engineering Mechanics*, Trans. ASCE, in print.

Straub D., Der Kiureghian A. (2010b). Bayesian Network Enhanced with Structural Reliability Methods. Part B: Applications. *Journal of Engineering Mechanics*, Trans. ASCE, in print.

Straub D., Faber M.H. (2006). Computational Aspects of Risk Based Inspection Planning. *Computer-Aided Civil and Infrastructure Engineering*, **21**(3), pp. 179-192.

Straub D. (2009), Stochastic Modeling of Deterioration Processes through Dynamic Bayesian Networks, *Journal of Engineering Mechanics, Trans. ASCE*, **135**(10), pp. 1089-1099.

Straub D. (2010), Reliability updating with equality information. *Probabilistic Engineering Mechanics*, under review.

Straub D., M. T. Bensi, and A. Der Kiureghian (2008), Spatial Modeling of Earthquake Hazard and Infrastructure Performance Through Bayesian Networks, in *Proc. EM'08 conference*, University of Minnesota, Minneapolis.

Tang W. H. (1973), Probabilistic Updating of Flaw Information, *Journal of Testing and Evaluation*, **1**(6), 459–467.

Wen Y. K., and H. C. Chen (1987), On fast integration for time variant structural reliability, *Probabilistic Engineering Mechanics*, **2**(3), 156–162.

Yang J.N., and W. J. Trapp (1974). Reliability Analysis of Aircraft Structures under Random Loading and Periodic Inspection. *AIAA Journal*, **12**(12), pp. 1623-1630.