MODELLING UNCERTAINTY AND PERFORMANCE UPDATING: APPLICATIONS IN CHLORIDE INDUCED DETERIORATION

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Abstract

Deterioration, increase in demand and change in utilisation of the transport infrastructure have induced an unknown level of risk in their use. Predicting future condition and reliability of the high value assets, such as bridges, is vital for their effective management and efficient use of resources. Predictive deterioration modelling and health monitoring systems both have limitations on their use and abilities in regard to prognosis. A powerful decision support tool may be developed by combining information obtained through structural health monitoring with probabilistic performance prediction models. A performance updating methodology is presented in this paper focusing on the concrete structures prone to chloride induced deterioration. It is concluded that a methodology combining information from the two sources would benefit the management of deterioration prone structures. Confidence regarding predicted performance of the structure can be significantly improved through the performance updating methodology presented in this paper.

Keywords: performance updating, concrete deterioration, structural health monitoring

1. INTRODUCTION

Highway transportation system is an important asset for the sustainable development of any society and is considered to be the backbone for economic growth of any country. Bridges constitute a vital part of the transportation system. The lifetime performance of these high value asset structures is vital for the sustained performance of the highway transportation system. Maintenance budget in many countries is either approaching or have already exceeded the budget for new development. Deterioration of bridges has been a hot subject amongst researchers since last three decades. The aim of prognosis, for the rational management of deteriorating structures, lead to the development of predictive models for deterioration. Concrete has been widely used in the construction of bridges around the globe. In the UK, about 65% of the motorway and trunk road bridges are either reinforced or prestressed concrete bridges (Mahut and Woodward, 2005). Deterioration of concrete bridges is primarily attributed to the corrosion of reinforcement, which is generally due to either chloride attack or carbonation (e.g. Basheer et al. 1996).

2. PREDICTIVE MODELING FOR CHLORIDE INDUCED DETERIORATION

Modelling of the chloride induced deterioration processes in concrete have been approached in literature using a variety of methods, such as based on Fick's 2nd law of diffusion, using Markov chain process, using Neural network models, modified solution of Fick's law assuming a fixed amount of surface contents or varying certain boundary conditions, modelling diffusion using Nernst-Einstein equation, modelling using experimental data of cracked concrete, and diffusion as a combination of Kundson and Viscous flow. The models range from empirical (based entirely on experimental results) to scientific (based entirely on scientific principles and physical laws) including a wide range of semi-empirical models (based on simplified scientific models that are calibrated through laboratory or field experiments). Several benchmark studies have been carried out to standardize the chloride ingress models, e.g. HETEK (1996) and DURACRETE (1998) but consensus regarding any particular phenomenon to be used for the modelling has not yet emerged. However, the majority of researchers are using Fick's diffusion law as a representative phenomenon. The fact that deterioration is a time dependent phenomenon (e.g. Stewart & Rosowsky, 1998) adds complexity in the modelling process. Uncertainty in the variables involved in the deterioration process is generally modelled using random variables. Spatial variability of the deterioration process and lack of knowledge regarding its details also contributes towards the complexity in modelling deterioration and associated uncertainty. The amount of uncertainty in the chloride induced deterioration is significant and limits the applicability of the predictive models for long range predictions. A typical model for the time to corrosion initiation based on Fick's second law of diffusion is presented in Eq. (1).

$$T_I = \frac{E_{\text{mod}} X^2}{4D\left[erfc^{-1}\left(\frac{C_{th}}{C_o} \right) \right]^2} \qquad (1)$$

Where T_I is the time to corrosion initiation at any given depth X; D, C_o, C_{th}, and E_{mod} represent the effective diffusion coefficient, surface chloride concentration, threshold chloride concentrations and model uncertainty factor respectively.

3. HEALTH MONITORING SYSTEMS

In a distinct, but related strand of research, health monitoring methods are being developed to monitor the performance of deteriorating structures. These range from very simple non-destructive methods (such as half cell measurements) to more sophisticated technology such as corrosion risk sensors possibly with remote sensing capability. These structural health monitoring (SHM) methods can provide real-time information on the deterioration characteristics of structures. There are, however, limitations associated with these methods, e.g. the information is limited to specific locations at which the sensors are installed, the accuracy is limited depending on the sensor type being used and parameter being monitored, and these are costly compared to other assessment methods. There are several other issues that must be addressed to facilitate the effective use of, and gain full benefits from, SHM. These include optimum number of instrumentation locations, type of data obtained through SHM (i.e. discrete vs. continuous) and methods to interpret the data (relation between the parameter being monitored and the parameter under consideration), methods to handle misinterpreted and unexpected results (if SHM results in erroneous or unexpected output), and procedures to incorporate spatial variability, etc.

The limitations of predictive modelling and those associated with the use of SHM (highlighted in Sec. 2 and above) can be considerably reduced by combining the two effectively. This can be achieved through performance updating.

4. PERFORMANCE UPDATING

A framework has been proposed in (Rafiq et al. 2004), which combines the information obtained from SHM with predictive deterioration modelling to improve the confidence in the predicted performance. At the heart of this framework is a Bayesian updating process which has the ability to incorporate information obtained from different sources at different point-in-time during long service lives, e.g. either from detailed inspections and monitoring or even from the qualitative assessment methods i.e. visual inspections or service records, etc. These techniques had a significant impact in nuclear plants assessment and in health care systems. More recently, these have been used successfully in offshore structures and steel bridges, etc, for the planning and optimisation of inspection and maintenance schedules. The advantages of the performance updating have been demonstrated in this paper through its application in the concrete structures subjected to the chloride induced deterioration.

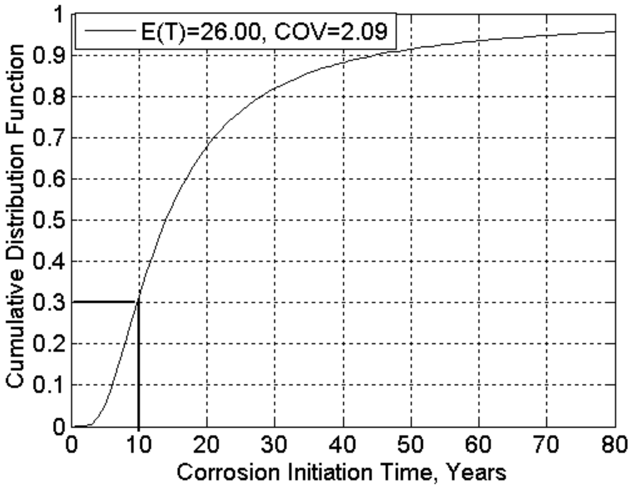
5. APPLICATION IN CHLORIDE INDUCED DETERIORATION

In order to demonstrate the effectiveness of the proposed updating methodology in gaining confidence in performance prediction, a simple bridge element such as a beam, slab or cross-girder is considered here, which is subjected to the chloride induced deterioration through winter salts.

5.1. Prior predictive deterioration model

Chloride induced deterioration of reinforced concrete structures is divided into two distinct phases; initiation and propagation (Tuuti, 1980). Both limit states have been used extensively in literature for the performance prediction. The focus, in this paper, has been on the initiation phase of the deterioration process. Mathematical form of the predictive model for this case (as discussed in Sec. 2) is presented by Eq. 1. Due to uncertainties in the quantification of these parameters, probabilistic approach for deterioration modelling is generally adopted, e.g. Thoft-Christensen et al. 1996. The distribution characteristics for the input random variables and the resulting distribution for the corrosion initiation time at 40mm depth (assumed rebar location) is shown in Fig. 1.

This curve can be interpreted in two different ways. The ordinate gives the probability that corrosion initiation at rebar level is reached up to any particular point in time (abscissa). If an acceptable (tolerable) target probability can be specified, the curve could be used to estimate the point in time at which certain management actions are to be taken (e.g. if a target probability of 0.3 is considered, actions would be taken after 10 years). On the other hand, the ordinate may be interpreted as the fraction of the area of a member exhibiting corrosion activity normalized by the total area. In this case, the target (or threshold) would represent the maximum corrosion damage tolerated for any particular member or structure.



Models for input random variables

C_o: Normal (μ = 3.5kg/m^3, COV=0.5)
C_{th}: Uniform (0.6 – 1.2 Kg/m^3)
D: Normal (μ=5x10^{-5} m^2/Yr, COV = 0.2)
Emod: Lognormal (μ=1.0, COV=0.25)
X: Normal (μ=40mm, COV = 0.1)
X_i: Normal (μ= 10, 20 and 30mm fully correlated, σ = 1mm)
T_{ini} = 0.1 years

Figure 1: Distribution for the corrosion initiation time.

5.2. Health monitoring systems

During the initiation phase, the corrosion risk of a reinforced concrete structure can be monitored through either chloride content measurements, or by measuring the penetration of the threshold chloride contents, in the cover concrete. Chloride measurement probes have been developed though they appear to still be in the testing and validation stage. Corrosion risk probes have also been developed, and instruments available for this include anode ladder arrangement, metallic nail system and expansion Ring System.

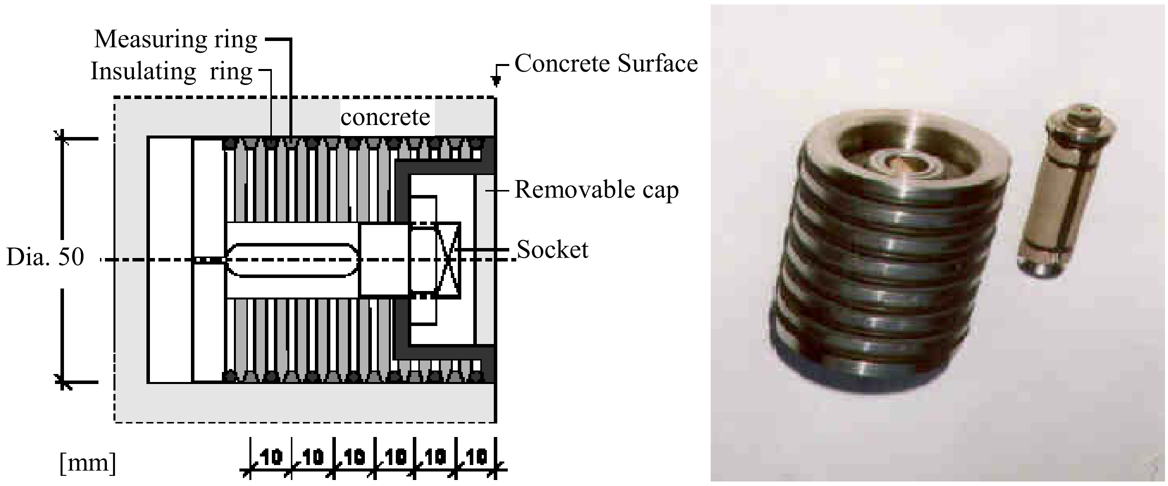


Figure 2: Expansion Ring System (Raupach and Schiβl, 2001)

The ladder arrangement can be installed in new structures or during repair works in existing structures. Expansion ring and Metallic nail systems can also be installed into existing structures without damaging the existing concrete cover. The working principle for all three systems is identical. Small pieces of steel are installed at various known depths into the cover concrete and the corrosion activity of these pieces is monitored. A curve of the corrosion penetration depth (obtained from the monitoring) is plotted against time, which is then extrapolated to predict the time to corrosion initiation at the rebar level.

5.3. Performance updating

For the purpose of updating, two possible outcomes are possible from the sensors discussed in the previous section. These are;

- Passivity confirmation at the sensor location at the time of monitoring, or
- Confirmation of corrosion activity at the sensor location at the time of monitoring.

Performance (in this case, time to corrosion initiation at rebar level) updating is achieved assuming 'n' number of sensors along the depth of the cover concrete. The expression used for updating is shown in Eq. 2, details of which can be found in Rafiq (2005).

$$F_T''(t) = P\left[\frac{[T_I(X = X_c) \le t]\bigcap_{i=1}^{n}[M_i \le 0]\bigcap_{i=1}^{n+1}[M(X_i) > 0]}{\bigcap_{i=1}^{n}[M_i \le 0]\bigcap_{i=1}^{n+1}[M(X_i) > 0]}\right] \qquad (2)$$

Where X_i = depth of sensor no. i from the concrete surface = X_c (cover depth) for i = n+1
$T_I(X = X_i)$ = priori predicted initiation time at depth X_i.
$M(X_i)$ = safety margin for expected corrosion initiation time at depth X_i from the surface of concrete at any time $t = t_a$.
= $T_I(X = X_i) - t_a$, when passivity is confirmed at depth X_i.
= $T_I(X = X_i) - (T_{Ii} - t_{int})$ when corrosion has initiated at depth X_i and time to corrosion initiation of sensor i, T_{Ii} becomes known.
M_i = Safety margin between predicted and actual initiation time for corrosion, when the time to corrosion initiation of sensor i becomes known.
= $T_I(X = X_i) - T_{Ii}$ and
= 0 for passivity confirmation case.
T_{Ii} = time at which initiation is detected by the sensor i.
t_{int} = time interval between the two events i.e. 'corrosion initiation confirmation' and 'passivity confirmation' that reflects the inability of monitoring instruments to detect exact corrosion initiation time.

5.4. Results and Discussions

The prior and updated (posterior) distributions for the 'corrosion initiation time' are plotted in Figure 3, for the both 'initiation confirmation' (Fig 3a) and 'passivity confirmation' case (Fig 3b). The reduction in uncertainty can be quantified by comparing coefficient of variations of the prior and posterior distributions. It can be seen from these figures that uncertainty is reduced continuously as more information becomes available, be it in the form of confirmation of passivity or in detecting initiation at sensor locations but the reduction is more pronounced for initiation confirmation case when the actual time to initiation at sensor location becomes available.

The percentage reduction in COV, with one sensor in position, is around 76 % and is practically constant regardless of the time to corrosion initiation at the sensor level (see Fig.

3a). In the case of confirmation of passivity, the COV reduces continuously with time and approaches 50% after about 4 years (Fig. 3b).

Based on the prior information, the time of first intervention on the bridge is 4.9, 6.0 and 8.0 years for the 5%, 10% and 20% distribution fractile respectively. These intervention times for different cases of passivity confirmation and sensor initiation times are summarised in Fig. 4.

For example, it can be seen that the time to corrosion initiation at rebar level (using the 10 % distribution fractile) changes from 6.0 years (prior information) to about 8 years (if the corrosion initiation is detected at the sensor location, at 10mm cover depth, after 1 year) or 12 years (if passivity is confirmed by the 10mm sensor after 1 year). As a result, the first intervention on the bridge (e.g. detailed inspection using half cell survey etc) can be brought forward or postponed accordingly. These results, of course, are dependent upon selected fractiles and will change depending upon the chosen fractile value.

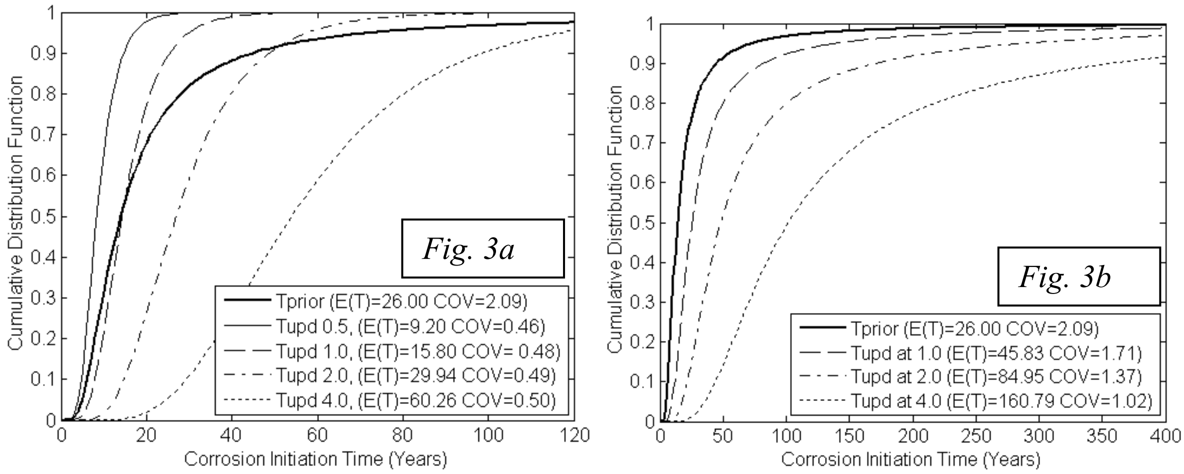


Figure 3: Posterior corrosion initiation time at rebar level

a) Initiation confirmation case *b) Passivity confirmation case*

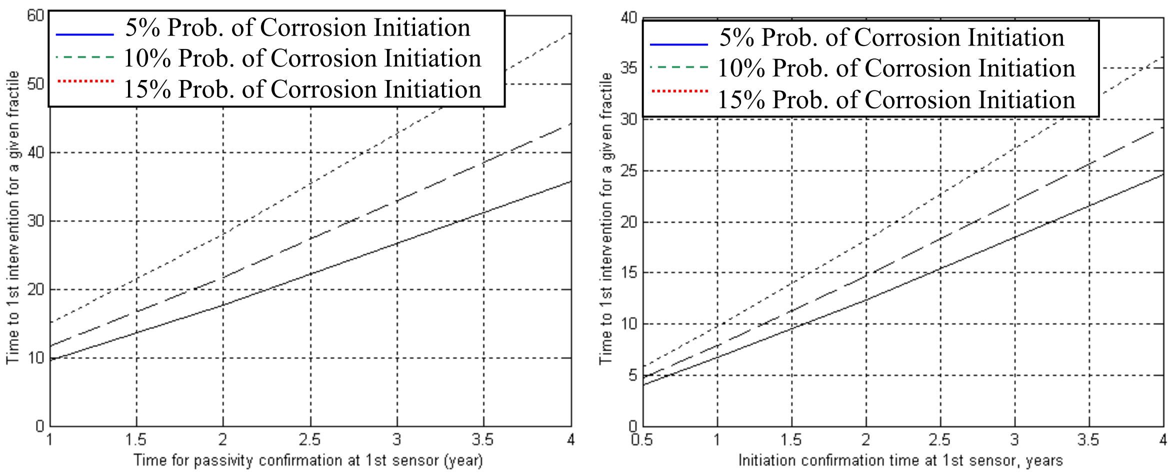


Figure 4: Effect of Sensor results on the Time to first intervention

In order to establish the robustness of the methodology for different input models, sensitivity studies of different input parameters on the corrosion initiation times have been carried out. The results for the sensitivity study are presented in detail in Rafiq (2005).

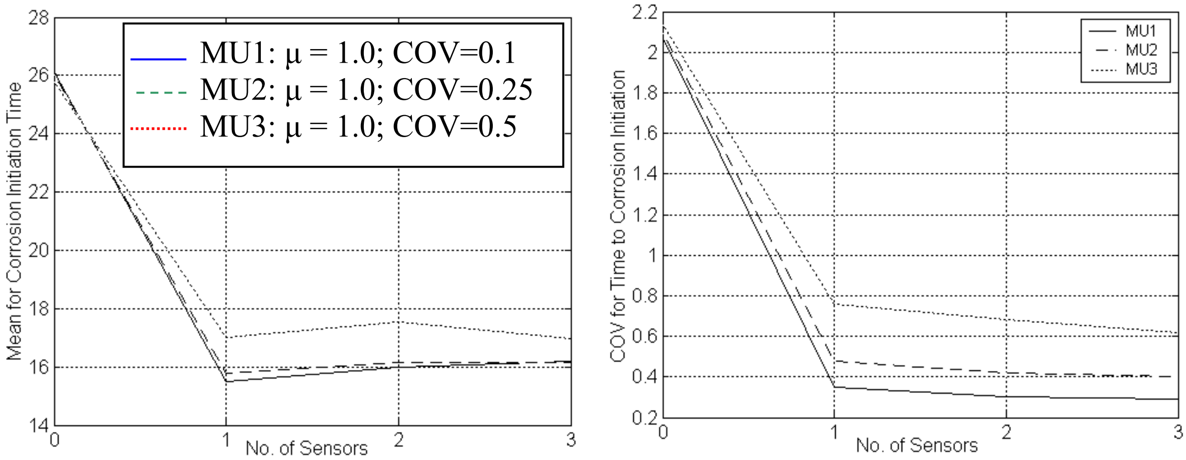


Figure 5: Effect of number of sensors in reducing uncertainty for time to corrosion initiation.

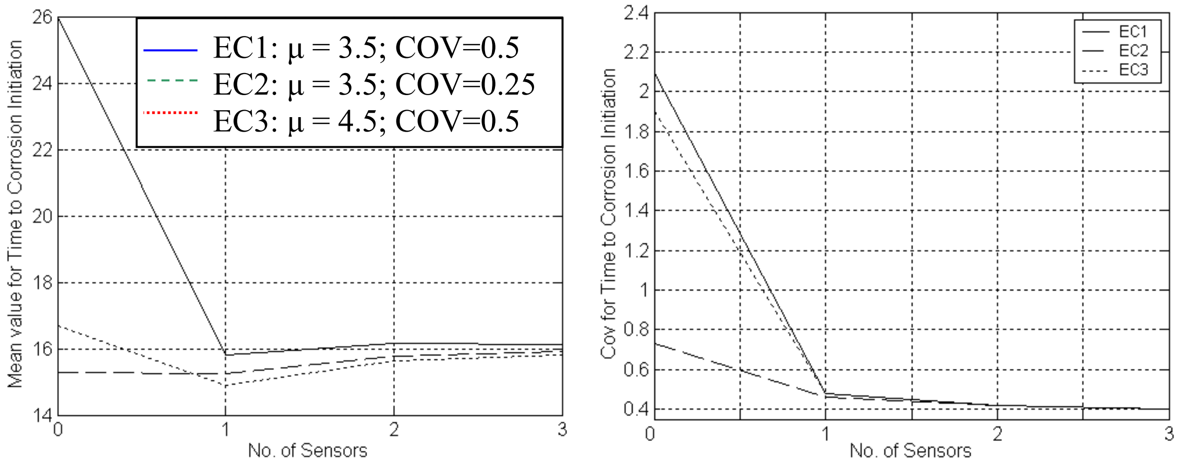


Figure 6: Effects of no. of sensors on uncertainty associated with exposure conditions.

Two distinct types of behaviour have been identified. In both cases, the COV of the corrosion initiation time is reduced with the increase in the number of sensors, indicating increase in confidence. However, for the results shown in Fig. 5, which refer to different assumptions for the model uncertainty distribution, the posterior COV takes different values for various input models whereas for the results shown in Fig. 6, which refer to different assumptions regarding exposure conditions, the posterior COV for various input models converges to a single value.

6. CONCLUSIONS

Predicting future condition and reliability of the deteriorating systems is vital for their effective management. The information (both qualitative and quantitative) obtained through visual inspections, NDE and HMS cannot be used explicitly for the prediction of future performances. Similarly uncertainties in the input parameters of the predictive models limit their effective use in several applications. Combining the two areas can provide a powerful tool that can be used to optimise the decisions regarding maintenance and management of deteriorating systems. A methodology based on Bayesian event updating framework is presented in this paper and its application for the effective integration of data obtained through HMS and predictive modelling is shown through an example of a concrete bridge element subject to chloride induced deterioration. It has been shown that the proposed methodology may significantly increase the confidence in the predicted performance by combining the information obtained through HMS and the predictive deterioration models. Of course, the results of such studies are limited by our ability to develop predictive models and the characteristics of the considered monitoring systems. Further work is needed in this area such as characterisation of available monitoring systems, e.g. in terms of accuracy, resolution and repeatability, etc, is necessary to improve confidence in the predictions of such studies.

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