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M. Imran Rafiq , Toula Onoufriou & Marios Chryssanthopoulos

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Sensitivity of uncertainties in performance prediction of deteriorating concrete structures

M. IMRAN RAFIQ*, TOULA ONOUFRIOU and MARIOS CHRYSSANTHOPOULOS

School of Engineering, University of Surrey, Guildford, Surrey, GU2 7XH, UK

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Deterioration models for the condition and reliability prediction of civil infrastructure facilities involve numerous assumptions and simplifications. Furthermore, input parameters of these models are fraught with uncertainties. A Bayesian methodology has been developed by the authors, which uses information obtained through health monitoring to improve the quality of prediction. The sensitivity of prior and posterior predicted performance to different input parameters of the deterioration models, and the effect of instrument and measurement uncertainty, is investigated in this paper. The results quantify the influence of these uncertainties and highlight the efficacy of the updating methodology based on integrating monitoring data. It has been found that the probabilistic posterior performance predictions are significantly less sensitive to most of the input uncertainties. Furthermore, updating the performance distribution based on 'event' outcomes is likely to be more beneficial than monitoring and updating of the input parameters on an individual basis.

Keywords: Bayesian updating; Chloride induced corrosion; Reinforced concrete structures; Health monitoring; Sensors

1. Introduction

In developed countries such as the United Kingdom, large parts of the civil infrastructure systems have been in place for many years. As a result, attention is now being focused on the maintenance and repair of these existing facilities. In recent years, significant attention has been given to the highway and railway bridges. As such bridges are subjected to a continuous increase in loading frequency and severity, and are exposed to harsh environmental conditions, they often decay at rates higher than envisaged during the original design.

Uncertainties associated with the nature and rate of deterioration, the demand (past, present and future) and the actual performance of these structures are considerable and subject to changes during their service life. Thus, infrastructure engineering and decision-making are of increasing importance to the bridge community. Predicting the future condition and reliability of these structures for a foreseeable part of the remaining service life is vital for their effective management. Research in this area has led to the development of a number of predictive models (scientific, semi-empirical and empirical) for a wide range of materials and exposure conditions. These models are now reaching a state of maturity even though they contain numerous assumptions and simplifications. Furthermore, the input parameters of these models are fraught with uncertainties (both epistemic and aleatoric) leading to the increasing use of probabilistic approaches for the assessment of these high value assets. Due to the considerable amount of uncertainties in the deterioration processes, these models are of limited practical use and are useful only for short-range predictions; Vu and Stewart (2000) have suggested that these models can only be used for obtaining predictions for 5–10 years into the future.

The continuous development in the field of sensing and measurement technology has now made it possible to

*Corresponding author. Email: m.rafiq@surrey.ac.uk

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obtain structure-specific information regarding loading, its effects, and the nature and rate of deterioration. This information can be used to improve the quality of prediction obtained through mathematical models by identifying and reducing the areas of uncertainty. A Bayesian methodology has been developed by the authors that can incorporate the information obtained through health monitoring systems within a reliability based performance assessment of structures with the view of increasing confidence in performance prediction by reducing associated uncertainties. The procedure for a 'point-in-space' case is presented in Rafiq *et al.* (2004), and is extended in Rafiq *et al.* (2005) to incorporate information from multiple sensors installed at various locations of the member/structural system.

A number of deterioration models are available in the literature for each particular deterioration phenomenon (based on one or more physical processes). There are also differences in the modelling of their input parameters that have a strong influence, due to uncertainty propagation, on the output, i.e. on the predicted performance (Enright and Frangopol 1998). An extensive sensitivity study on the prior and posterior performance prediction (i.e. before and after incorporating data obtained through health monitoring systems) of bridges prone to chloride-induced deterioration is presented in this paper. The effect of different values for the probabilistic distribution parameters of random input variables, such as diffusion coefficient and threshold chloride concentration, is quantified. The uncertainty related to a model variable and to health monitoring system (instrument and measurement uncertainty) is also investigated.

2. Probabilistic model for chloride-induced deterioration

Chloride-induced deterioration is considered since it has been identified as the principle cause of deterioration in highway bridges for the UK stock (Wallbank 1989) and similar conclusions have been reached elsewhere. There appears to be a developing consensus in the research community regarding the modelling of chloride-induced deterioration using Fick's second law of diffusion. A typical predictive model based on this law is presented in equation (1).

$$C(X,t) = C_o\left[1 - erf\left(\frac{X}{2\sqrt{Dt}}\right)\right] \tag{1}$$

where $C(X,t)$ = chloride contents at depth X (from the concrete surface) and time t; C_o = surface chloride contents; and D = effective diffusion coefficient.

More elaborate deterioration models—including absorption (Chryssanthopoulos and Sterritt 2002)—have also been developed, but lack of field data is, at present, restricting their validation and use. Rearranging equation (1) and replacing $C(X,t)$ with the critical threshold chloride concentration for corrosion initiation, C_{th}, leads to

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

where $T_I(X)$ is the time to corrosion initiation at any depth X from the surface and E_{mod} is a variable introduced to represent the modelling uncertainty. Since the values for the parameters in equation (2) are not known with certainty, a probabilistic approach has been proposed (Thoft-Christensen *et al.* 1996) resulting in a probability distribution for the time to corrosion initiation. The distribution types and their parameter values for the basic random variables are discussed below. The posterior time to corrosion initiation based on additional information obtained through structural health monitoring is given by Rafiq *et al.* (2004).

$$F''_T(t) = P\left(\frac{(T_I(X = X_c) \leqslant t) \cap_{i=1}^{n} M_i \leqslant 0 \cap_{i=1}^{n+1} M(X_i) > 0}{\cap_{i=1}^{n} M_i \leqslant 0 \cap_{i=1}^{n+1} M(X_i) > 0}\right) \tag{3}$$

where X_i = depth of sensor i from concrete surface = X_c (cover depth) for $i = n+1$;
n = total number of sensors;
$i = 1,2.\ldots,n$ representing sensor number at depth X_i;
$T_I(X = X_i)$ = *priori* predicted initiation time at depth X_i;
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.
$M(x_i)$ = safety margin for expected corrosion initiation time at depth x_i from the surface of concrete at any time $t = t_a$;
$= E_{\mathrm{mod}}\ T_I(X = X_i) - t_a$, when passivity is confirmed at depth X_i;
$= E_{\mathrm{mod}}\ T_I(X = X_i) - (T_{Ii} - t_{\mathrm{int}})$ 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;
$= E_{\mathrm{mod}}\ T_I(X = X_i) - T_{Ii}$ and
$= 0$ for passivity confirmation case.

3. Modelling of deterioration variables

3.1 *Modelling uncertainty for diffusion model, E_{mod}*

The modelling uncertainty variable, E_{mod}, represents the uncertainty associated with the mathematical representation of the selected governing physical phenomenon. It could also account for the absence of explicit models to represent other physical phenomena involved. As is well known, the ingress of chloride is a complex process. Different processes have been proposed to mimic chloride penetration into concrete and a variety of scientific and semi-empirical models have been put forward. Although equation (2) is widely used by those advocating diffusion as the dominant process, the distribution type and parameters for the model uncertainty are not well established in the literature. Lentz *et al.* (2002) have used lognormal distribution with mean and coefficient of variation (COV) of 1.0 and 0.1, respectively, whereas Faber and Sorensen (2001, 2002) have used lognormal distribution with mean and COV of 1.0 and 0.05, respectively. Comparison of actual time to corrosion initiation (published in the literature) with predicted values using equation (2) point towards higher modelling uncertainty levels. The distributions of modelling uncertainty considered in the present sensitivity analysis are

MU1. Lognormal; mean = 1.0, COV = 0.1
MU2. Lognormal; mean = 1.0, COV = 0.25
MU3. Lognormal; mean = 1.0, COV = 0.5

3.2 *Exposure conditions*, C_o

Three main sources of chloride in concrete include chloride cast in concrete (e.g. plasticizers, etc.), the influence of a marine environment and de-icing salts. Modern material specifications limit the amount of chloride cast into concrete. Stewart and Rosowsky (1998) have reported that structures within a 3 km range of the coast are affected by the marine environment to a varying degree depending on the distance from the coast.

Surface chloride concentration, with de-icing salts being a dominant source, is dependent on the type of concrete and exposure conditions that is a function of amount of salts sprayed, weather conditions (amount of snow, rain and wind) and traffic flow etc. Hence a probabilistic model is used to describe the surface chloride concentration. Table 1 summarises some recently used surface chloride concentration models. A graph presented by Vu and Stewart (2000) shows that the mean value is, as might be expected, location dependent and hence would be different for different networks of bridges.

Based on the above discussion, the following three cases have been considered in the sensitivity studies. All three cases would be typical of a bridge in an environment of average severity as a result of de-icing salt application.

EC1. Lognormal; mean = 3.5 Kg/m^3, COV = 0.5
EC2. Lognormal; mean = 3.5 Kg/m^3, COV = 0.25
EC3. Lognormal; mean = 4.5 Kg/m^3, COV = 0.5

3.3 *Threshold chloride concentration*, C_{th}

Threshold chloride concentration is a function of material and workmanship factors, i.e. type of concrete, amount of cement contents and w/c ratio, micro-cracks at steel – concrete interface, temperature and humidity, etc. Different values for the threshold chloride concentrations have been reported in the literature. Lentz *et al.* (2002) have used normal distribution with mean and COV of 2.3 Kg/m^3 and 0.3, respectively. Similarly Thoft-Christensen (2000) have used normal distribution with mean and COV of 0.90 Kg/m^3 and 0.15, respectively. Stewart and Rosowsky (1998) modelled it as a uniform distribution between 0.6 and 1.2 Kg/m^3. The same distribution has been used by Vu and Stewart (2000, 2002). Faber and Sorensen (2001) have used lognormal distribution with mean and COV of 0.45 Kg/m^3 and 0.33, respectively.

Kirkpatrick *et al.* (2002) performed sensitivity analysis of threshold chloride concentration on the predictive model using a triangular distribution with lower limit of 0.6 Kg/m^3 and upper limit of 1.2, 2.0, 3.0, 4.0 and 5.0 Kg/m^3, respectively. Considerable variation in the output was

Table 1. Summary of recently used models for surface chloride concentration.

Reference	Type	Mean (Kg/m^3)	St. dev. (Kg/m^3)
Thoft-Christensen *et al.* (1996)	Normal	3.24	0.22
Stewart and Rosowsky (1998), Vu and Stewart (2000, 2002)	Lognormal	3.5	1.75
Faber and Sorensen (2001, 2002)	Lognormal	μ_{cs} μ_{cs} = Normal ($\mu = 9.2$, $\sigma = 0.92$)	1.84
Lentz *et al.* (2002)	Lognormal	μ_{cs} μ_{cs} = Normal ($\mu = 5.52$, $\sigma = 0.46$)	0.92
Lounis and Amleh (2004)	Lognormal	3.81	1.53

observed with different threshold chloride models. In this study, three different models are examined:

TC1. Uniform (0.6–1.2) $\mathrm{Kg/m^3}$; mean = 0.9 $\mathrm{Kg/m^3}$, COV = 0.19
TC2. Uniform (0.6–2.0) $\mathrm{Kg/m^3}$; mean = 1.3 $\mathrm{Kg/m^3}$, COV = 0.31
TC3. Normal; mean = 0.9 $\mathrm{Kg/m^3}$, COV = 0.17

3.4 *Workmanship and material quality*

The uncertainty associated with the quality of material and workmanship has a considerable effect on the expected performance of a concrete structure. Workmanship quality is reflected in the present study through the concrete cover uncertainty whereas the uncertainty in material quality is associated with the probabilistic model adopted for diffusion coefficient. These effects are correlated since a good level of workmanship generally would be associated with good concrete quality, and thus less variation in concrete cover. Hence, the probabilistic modelling for concrete cover and effective diffusion coefficient are considered in tandem.

3.4.1 Cover depth, X_c. Cover depth on highway bridges may vary significantly from the specified depths (Wallbank 1989). Investigations have shown that this variability is related to construction quality, i.e. steel fixing, formwork erection, concrete casting and a number of quality checks performed on site (Mirza and MacGregor, 1979, Morgan *et al*. 1982, Marosszeky and Chew 1990, Clark *et al*. 1997). It has been suggested that cover depth is significantly affected by contractor's practice. The average cover depth provided by some contractors is frequently greater than the design specification, while that of others is frequently below the specified value. No systemic variation is found between horizontal and vertical faces, but complex steel fixing can lead to low cover (Sterritt 2000).

3.4.2 Diffusion coefficient, D. Diffusion coefficient values have been reported in the literature to vary from 70 to 1350 $\mathrm{mm^2/year}$. Diffusion is a function of water to cement ratio, amount of cement and type of concrete, temperature and humidity in addition to workmanship quality, i.e. placing, compacting and curing, etc. (Page *et al*. 1981, Tuutti 1982, Thomas 1991, Liam *et al*. 1992, Maruya *et al*. 1994, Zhang and Gjorv 1996, Glass and Buenfeld 1997). Some researchers have argued that diffusion coefficient decreases with time, e.g. HETEK (1996). This variation is attributed to the hydration of cement but tends to become small a few years after construction (Bamforth and Price 1997). Vu and Stewart (2000) compared various diffusion coefficient models and recommended the use of a model developed by Papadakis *et al*. in 1996. The coefficient of variation of the diffusion coefficient is obtained through field data. Sensitivity analysis by Enright and Frangopol (1998) observed that the COV of the diffusion coefficient has a small effect on the corrosion initiation time.

Sterritt (2000) analysed field samples obtained from different published sources and came up with three broad categories related to concrete and workmanship quality, named 'good quality', 'average quality' and 'poor quality.' These are related to the diffusion coefficient and concrete cover and no attempt is made to relate these categories to concrete grades/classes. The diffusion coefficients and concrete cover models for these cases are given below and are also adopted in the current study.

WQ1. D_{Good} = Lognormal; mean = 5×10^{-5}, standard deviation = 1×10^{-5} $\mathrm{m^2/year}$; X_{Good} = Normal; mean = 40×10^{-3}, standard deviation = 5×10^{-3} m
WQ2. D_{Avg} = Lognormal; mean = 10×10^{-5}, standard deviation = 2×10^{-5} $\mathrm{m^2/year}$; X_{Avg} = Normal; mean = 40×10^{-3}, standard deviation = 10×10^{-3} m
WQ3. D_{Poor} = Lognormal; mean = 15×10^{-5}, standard deviation = 3×10^{-5} $\mathrm{m^2/year}$; X_{Poor} = Normal; mean = 40×10^{-3}, standard deviation = 15×10^{-3} m

3.5 *Instrument/measurement uncertainty*, $\mathrm{T_{int}}$

Monitoring the penetration of the threshold chloride concentration at various depths of concrete cover is used to update the time to corrosion initiation at the rebar level. Some common instruments used for this purpose are shown in figure 1. Their working principle is the same as that of a half cell.

When the chloride concentration increases beyond its threshold level at a certain cover depth, any steel at that depth depassivates and the negative potential and current value increases. By monitoring this variation in potential or current values, the time to corrosion initiation at the sensor location can be estimated. In general, a single potential/current value has been used to model the initiation of corrosion, e.g. Raupach (2002) used 400 mV and 10 uA as the limiting values to model corrosion initiation for expansion ring system (figure 1b). These values depend on the type of instrument being used. Table 2 summarises the limiting values for different electrodes.

It is evident from table 2 that a limiting potential value corresponding to corrosion initiation cannot be modelled accurately as it involves a degree of uncertainty. This uncertainty in modelling the limiting potential value can also be observed from the data published by Lentz *et al*. (2002) where, after half cell measurements, the steel bars were exposed to check the actual reinforcement condition. This additional uncertainty needs to be incorporated into the probabilistic methodology. One possible solution is to model the corrosion initiation using two limiting potential values. The first limiting potential would correspond to a very low probability of corrosion initiation while the second would correspond to a very high probability of corrosion initiation. The time required by the sensor to transit from first potential to the second, termed here as 't_{int}', represents instrument/measurement uncertainty. The value for 't_{int}' depends upon the chloride ingress rate, concrete quality and the difference between the upper and lower limiting potential values. From the curve of potential values versus time, presented by Raupach (2002), t_{int} can be approximated as 30 days. It is realised that until the sensors are used more widely these estimates should be treated as tentative. In addition, some degree of uncertainty would also exist due to the location of instrument/sensors in the concrete cover. This is incorporated using their location as a random variable (see table 3 for details).

The following values of t_{int} have been considered in order to study the effects of this variable on the posterior corrosion initiation time.

IU1. 0.05 year
IU2. 0.1 year
IU3. 0.15 year

4. Results and discussion

A typical structural element of a bridge (e.g. slab, beam or a cross beam, etc.) subjected to de-icing salts is considered. The probabilistic modelling for the remaining parameters of the corrosion initiation model are summarised in table 3. The sensors are assumed to be located at nominal depths of 10, 20 and 30 mm, while the reinforcement is located at a nominal depth of 40 mm.

The results for each case are presented in the following sub-sections. Monte-Carlo simulation with Latin-hypercube sampling is used to generate prior and posterior distributions for corrosion initiation time. The distributions in some cases are truncated only for plotting purposes.

4.1 *Modelling uncertainty for diffusion model*

The different distributions for the modelling uncertainty variable considered in the sensitivity analysis and the associated prior corrosion initiation times are plotted in figure 2. The probability density function for the distributions are also plotted in figure 2. It can be seen from the figure that the modelling uncertainty has a negligible effect on the prior time to corrosion initiation (represented by the COV of the distribution), e.g. increase in the COV for the

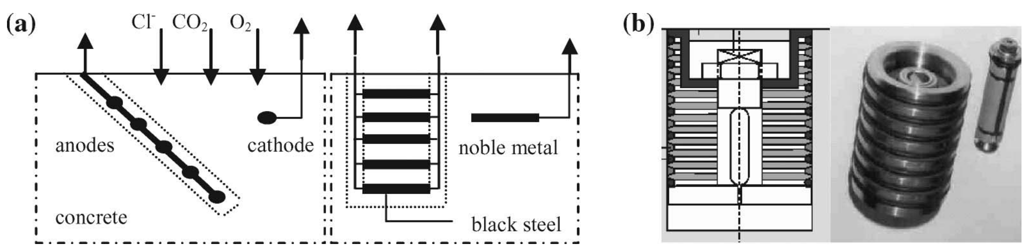

Figure 1. Instruments to monitor threshold chloride penetration in cover concrete; (a) ladder arrangement (Schieβl and Raupach1993); (b) expansion ring system (Raupach 2002).

Table 2. ASTM criteria for corrosion of steel in concrete (Broomfield 1997).

Copper/copper sulphate	Silver/silver chloride	Standard hydrogen electrode	Calomel	Corrosion condition
>-200 mV	>-106 mV	$>+116$ mV	>-126 mV	Low ($<10\%$ risk of corrosion)
-200 to -350 mV	-106 to -256 mV	$+116$ to -34 mV	-126 to -276 mV	Intermediate corrosion risk
<350 mV	<-256 mV	<-34 mV	<-276 mV	High ($>90\%$ risk of corrosion)
<-500 mV	<-406 mV	<-184 mV	<-426 mV	Severe corrosion

Table 3. Parameter type and distribution characteristics.

Parameter	Mean	COV	Distribution
X_i	10, 20 and 30 mm (fully correlated)	$\sigma = 1$ mm	Normal
t_{int}	0.1 years		Deterministic

prior time to corrosion initiation at rebar level is only 0.48% due to an increase in the COV for modelling uncertainty of 60% (i.e. from 0.1 to 0.25). Similarly, increase in the COV for the prior rebar corrosion initiation time is only 2.4% (i.e. from 2.08 to 2.13) for an increase in the modelling uncertainty of 100% (i.e. from 0.25 to 0.5). The reason for this small effect of E_{mod} on the total COV is due to the dominating influence of uncertainties in the estimation of other basic random variables i.e. X, D, C_{th} and C_o. The uncertainty associated with the posterior corrosion initiation time, however, is proportional to the modelling uncertainty as can be seen from figure 3 for various assumed sensor initiation times (at 10 mm cover depth), e.g. for the sensor initiation time of say 1.0 years, an increase in the modelling uncertainty of 60% (i.e. from MU1 to MU2 case) causes an increase in the COV of rebar corrosion initiation time of over 37%. Similarly, further increase in modelling uncertainty of 100% (i.e. from case MU2 to MU3) causes an increase in the COV of rebar corrosion initiation time of over 58%.

It can also be seen from figure 3 that the uncertainty associated with the rebar corrosion initiation time has been reduced considerably from its prior prediction, e.g. this reduction in COV for the case of MU2 is in the range of 76 to 78% depending on the sensor initiation times (i.e. from 2.09 for the prior case, to about 0.48 for the posterior case). The increase in mean value for the rebar corrosion initiation time is a linear function of the sensor initiation time as can be seen from figure 4. Another important conclusion from figure 4 is that the coefficient of variation of the posterior rebar corrosion initiation time is practically independent of the sensor initiation time. In the event that multiple sensors are installed along the cover depth, variation in the mean and COV for the posterior times to corrosion initiation at the rebar level can be seen in figure 5. The 'zero'

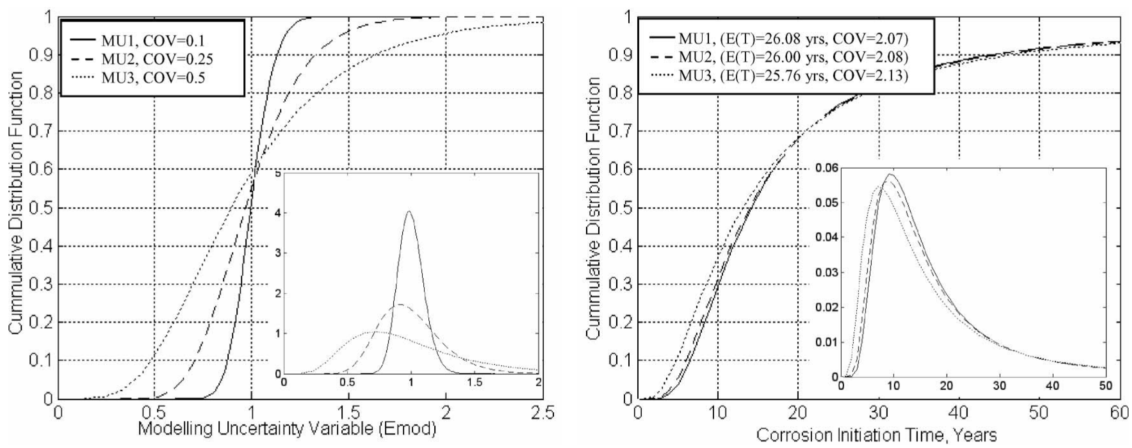

Figure 2. Modelling uncertainty distributions and rebar corrosion initiation times.

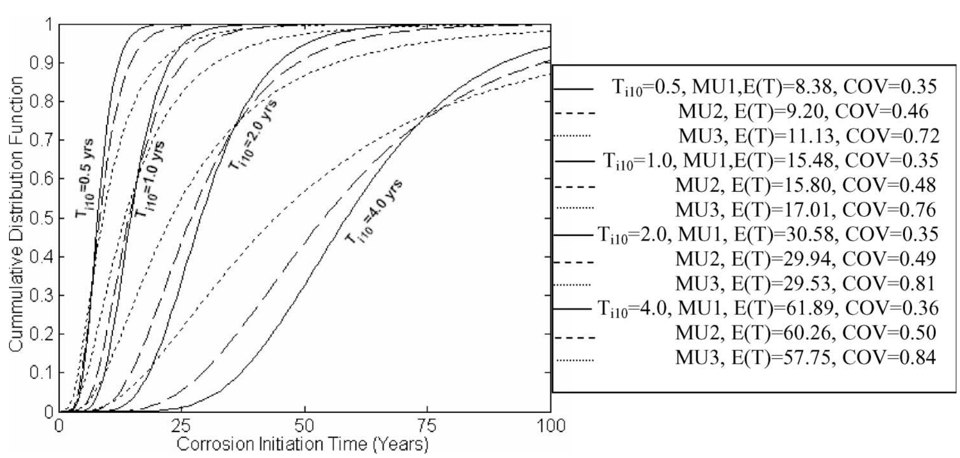

Figure 3. Posterior corrosion initiation times for various uncertainty levels and sensor initiation times.

sensor case corresponds to the prior time to corrosion initiation. Increase or decrease in the mean value for the time to corrosion initiation is strongly influenced by the actual initiation time at the sensor locations (initiation times assumed for the three sensors at 10, 20 and 30 mm depth are 1.0, 4.0 and 9.0 years, respectively) but are converging with the increase in number of sensors. This shows the effectiveness of updating in reducing epistemic modelling uncertainty. The coefficient of variation is also reducing with the increase in number of sensors (as is clear from figure 5). This reduction is considerable for the first updating but less so for subsequent updating. The difference in COV for different modelling uncertainty distributions is almost constant regardless of the number of sensors after the first updating. This provides a rationale for always striving for better predictive models, with modelling uncertainties as low as possible.

4.2 *Exposure conditions*

Models for different exposure conditions (in terms of chloride concentration at surface) and the associated prior distributions for corrosion initiation time at rebar level are shown in figure 6. The figure shows a significant difference in the distribution characteristics of prior corrosion initiation times for different exposure conditions. A reduction in the uncertainty associated with surface chloride concentration (i.e. Case EC2, where the COV is reduced by 50% from the Case EC1) not only has resulted in a reduction in the uncertainty of the corrosion initiation time, i.e. COV from 2.09 to 0.73 (about 65%) but also has significantly reduced its mean value, i.e. from 26.0 to 15.3 years (about 41%).

Similarly, an increase in the mean value of surface chloride concentration (more severe environment, Case EC3 compared to Case EC1) by about 29% causes a

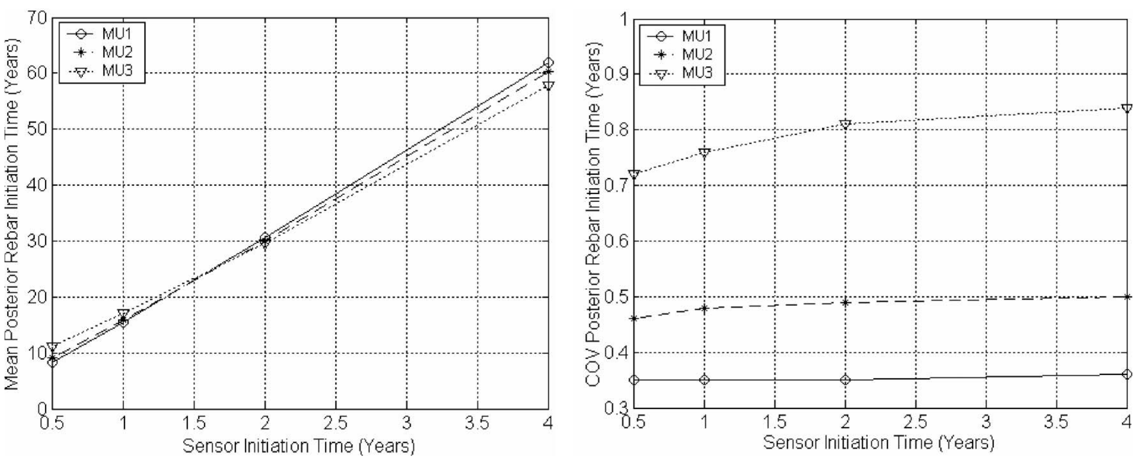

Figure 4. Mean and COV for posterior rebar initiation time vs sensor initiation time.

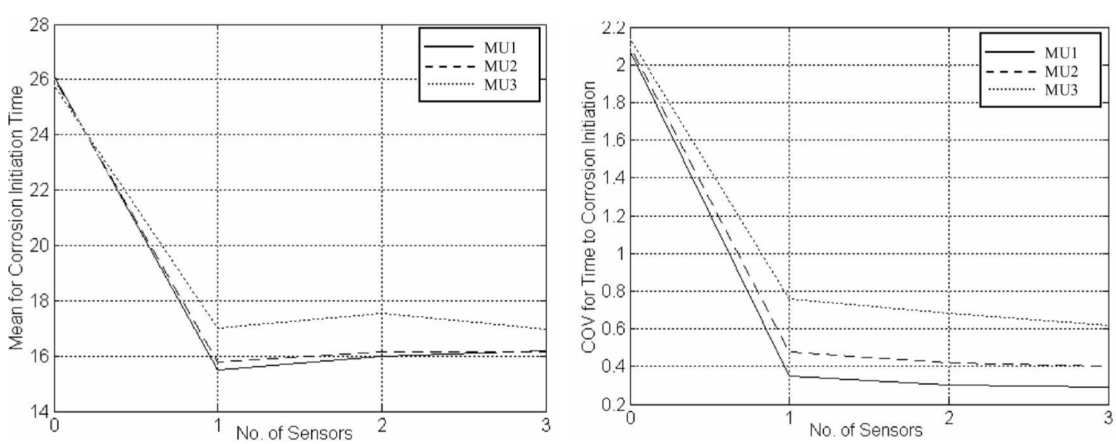

Figure 5. Effect of number of sensors in reducing uncertainty for time to corrosion initiation.

reduction in mean value of corrosion initiation time from 26.0 to 16.70 years (i.e. 36%). Only a slight reduction in uncertainty of corrosion initiation time (about 9%) is observed.

Figure 7 shows the posterior time to corrosion initiation at rebar level for various exposure conditions, and different sensor initiation times at 10 mm cover depth. The reduction in uncertainty associated with the posterior time to corrosion initiation is evident for all assumed sensor initiation times, e.g., for the case EC1, this reduction is in the range of 76% to 78% depending on the sensor initiation time. Similarly, for the cases EC2 and EC3, this reduction is in the range of 33% to 40% and 74% to 76%, respectively. Similar to the modelling uncertainty case, the rebar corrosion initiation time is a linear function of the sensor initiation time hence can be used to establish posterior corrosion initiation times for various sensor initiation times obtained in the field.

The uncertainty associated with posterior corrosion initiation time at rebar level is further reduced by the use of additional sensors along various depths of concrete cover as shown in figure 8. The assumed corrosion initiation times at the three sensors located at 10, 20 and 30 mm cover depth are 1.0, 4.0 and 9.0 years, respectively. Figure 8 clearly shows that the posterior distributions for time to corrosion initiation at rebar level for various exposure conditions have converged considerably (the mean value as well as the uncertainty). In other words, the posterior time to corrosion initiation is not very sensitive to uncertainties associated with exposure conditions. It can also be concluded from the above results that performance updating is likely to be more beneficial than monitoring and updating of exposure condition models.

Assuming 10% probability of corrosion initiation as the durability limit state, the time of first intervention on the bridge (or element under consideration) would be 6.1 years

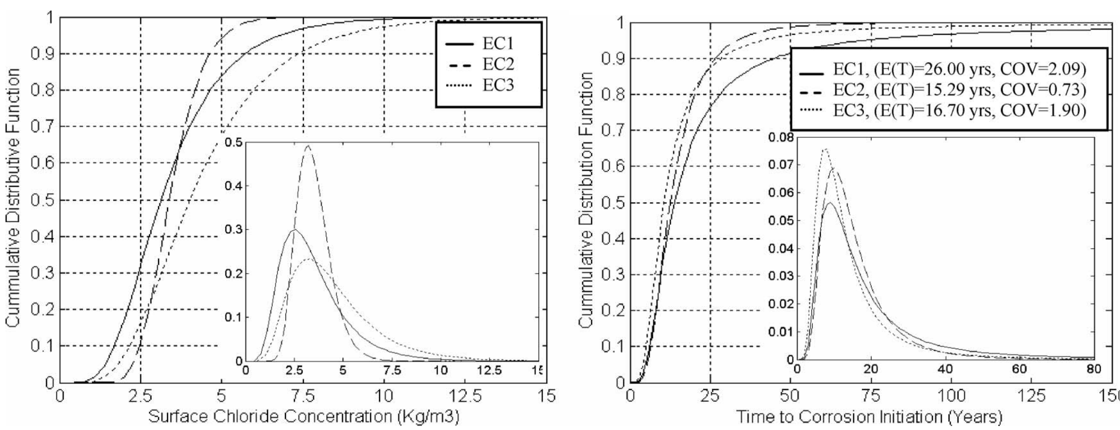

Figure 6. Models for different exposure conditions and prior corrosion initiation times at rebar level.

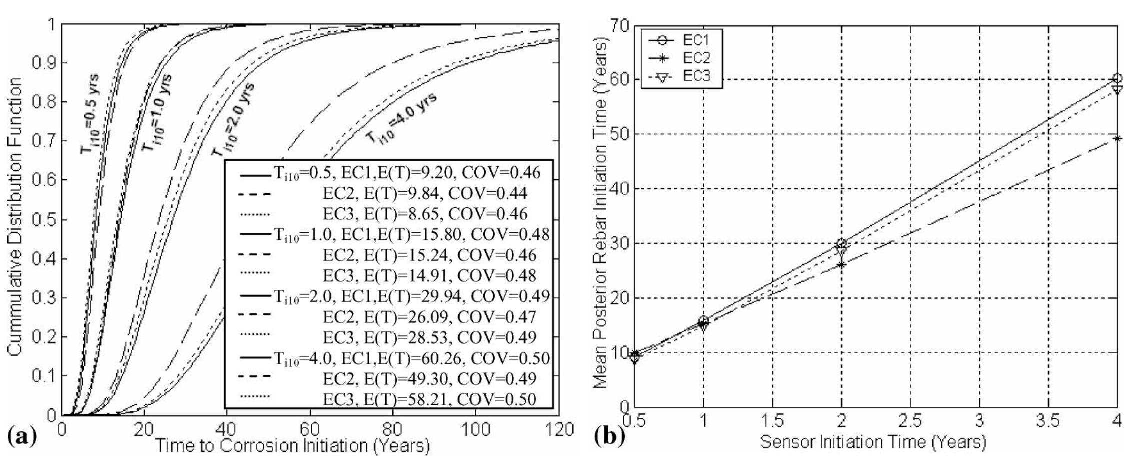

Figure 7. Posterior rebar corrosion initiation times for various exposure conditions and sensor initiation times; (a) CDF; (b) mean rebar initiation time vs. sensor initiation time.

for the EC1 case (figure 6). This time is increased to 6.4 years for the case where uncertainty is reduced by 50%, i.e. case EC2. Similarly time of first intervention would be reduced to 5.05 years if the mean surface chloride concentration is increased by 28.6%, i.e. case EC3.

The time of first intervention based on posterior corrosion initiation time would be 7.95, 7.88 and 7.48 for the cases EC1, EC2 and EC3, respectively for one sensor at 10 mm cover depth showing initiation at 1.0 year, which is sufficiently accurate for all practical purposes. Naturally, the range becomes even smaller in the presence of more sensors.

4.3 *Threshold chloride concentration*

Various models for threshold chloride concentration, C_{th}, and the associated prior corrosion initiation times at rebar level are shown in figure 9. It is clear from the figure that, for the same mean, the tail characteristics of the two distributions (uniform and normal) have no effect on the distribution of corrosion initiation time.

It can also be seen that increasing the upper limit for C_{th} from 1.2 Kg/m^3 (case TC1) to 2.0 Kg/m^3 (Case TC2), i.e. an increase in mean and COV of about 44% and 63%, respectively causes an increase in the mean for corrosion initiation time of about 98% while its COV remains practically unaffected. Similar results have been obtained by Enright and Frangopol (1998) and Kirkpatrick *et al.* (2002).

The posterior predicted time to corrosion initiation at rebar level for various initiation times at 10 mm cover depth and for different threshold chloride models are shown in figure 10. Similar to the other cases, the uncertainty in corrosion initiation time is reduced considerably for different hypothesized initiation times at sensor location (10 mm cover depth), e.g. the COV is reduced from 2.09 (prior case) to about 0.5 (posterior case). It can also be seen from figure 10 that the effect of

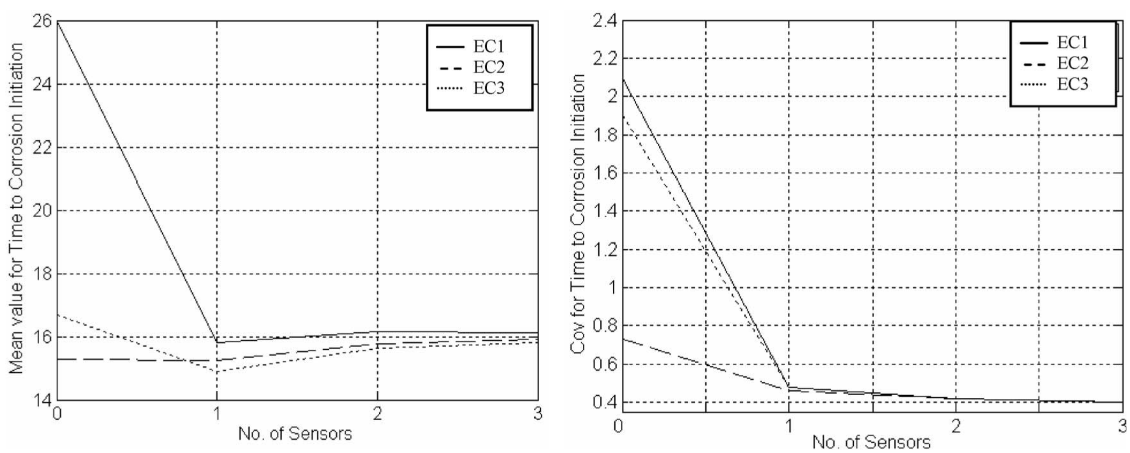

Figure 8. Effects of number of sensors in reducing uncertainty associated with exposure conditions.

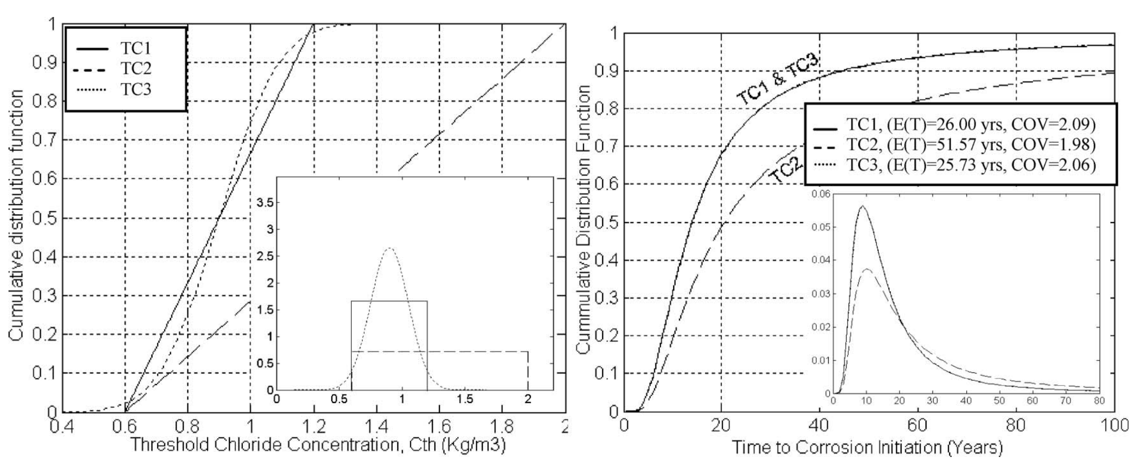

Figure 9. Different models for threshold chloride concentration and rebar corrosion initiation time.

uncertainty in modelling threshold chloride concentration is considerably reduced in the posterior predicted time to corrosion initiation and is reduced further by the installation of additional sensors along various depths within the concrete cover as shown in figure 11.

Figure 11 clearly shows that the mean and COV for posterior predicted corrosion initiation time is converging asymptotically to a single value, i.e. the uncertainty associated with modelling of threshold chloride is reduced by the effective use of data obtained through monitoring. From the above discussion it can be concluded that updating of the overall performance is likely to be more beneficial than obtaining additional information and hence improving the threshold chloride model prior to performance evaluation.

Based on the prior predictive model, the 'time to first intervention' on bridges, assuming 10% probability of corrosion initiation as the durability limit state, are 6.1, 7.5 and 6.13 years, i.e. a difference of 1.4 years between TC1 and TC2 case, which is reduced to 0.53 years (7.92 and 8.45 years for the first sensor initiated at year 1.0). This difference is further reduced to 0.36 years and 0.33 years by updating using the subsequent second and third sensors information, respectively.

4.4 *Workmanship and material quality*

Various models for diffusion coefficient and concrete cover considered in the sensitivity analysis are shown in figure 12 and the associated prior corrosion initiation times are shown in figure 13.

As can be seen, the reduction in quality (i.e. 100% increase in mean diffusion coefficient and 100% increase in COV of concrete cover) results in an early corrosion initiation (i.e. reduction of mean value (by about 44%) and an increase in uncertainty of corrosion initiation time (i.e. COV increase of

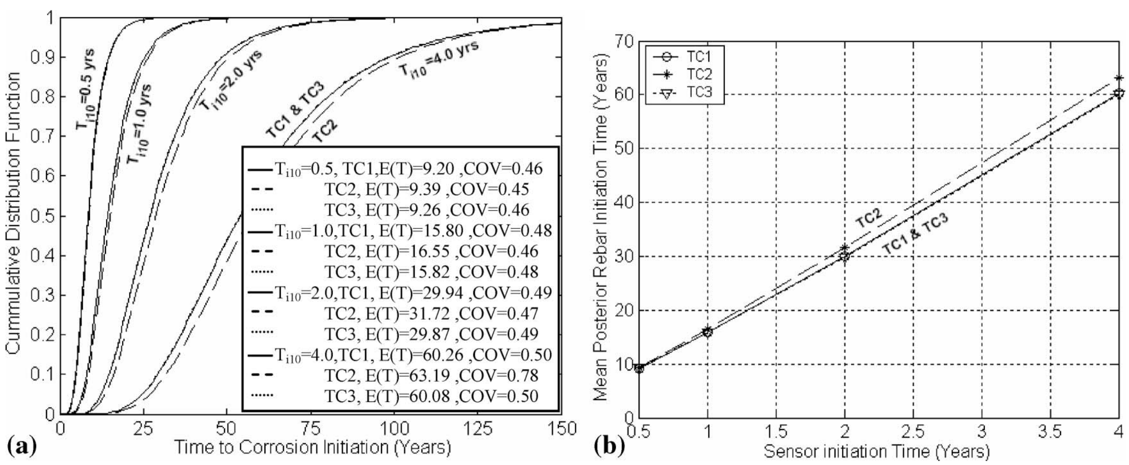

Figure 10. Posterior corrosion initiation time for different threshold chloride models and sensor initiation times; (a) CDF; (b) mean posterior rebar initiation time vs sensor initiation time.

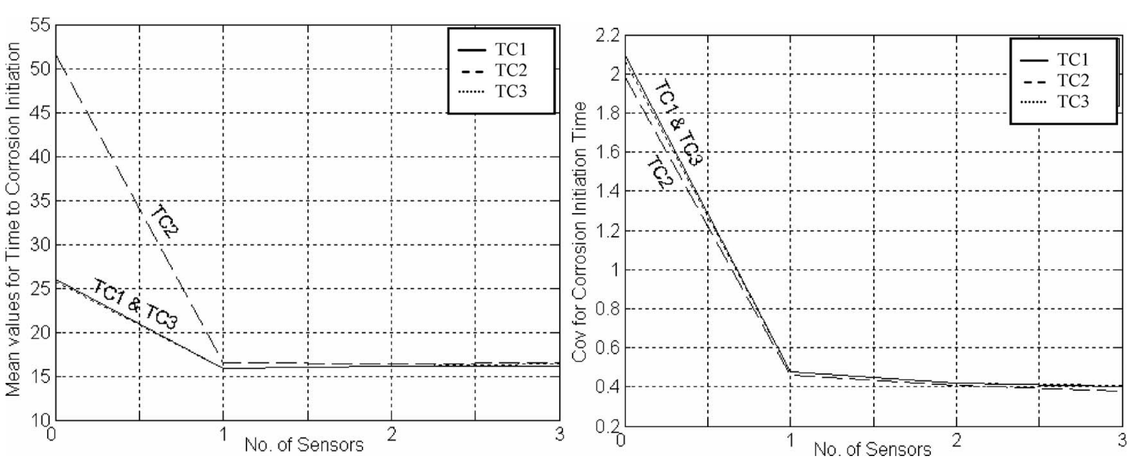

Figure 11. Effect of number of sensors in reducing uncertainties for various threshold chloride models.

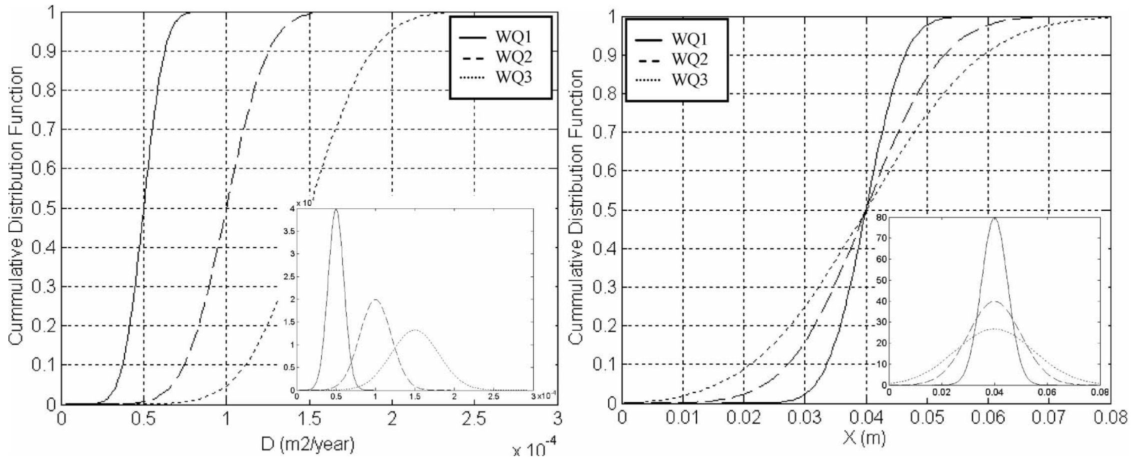

Figure 12. Various models of diffusion coefficient and concrete cover used for sensitivity analysis.

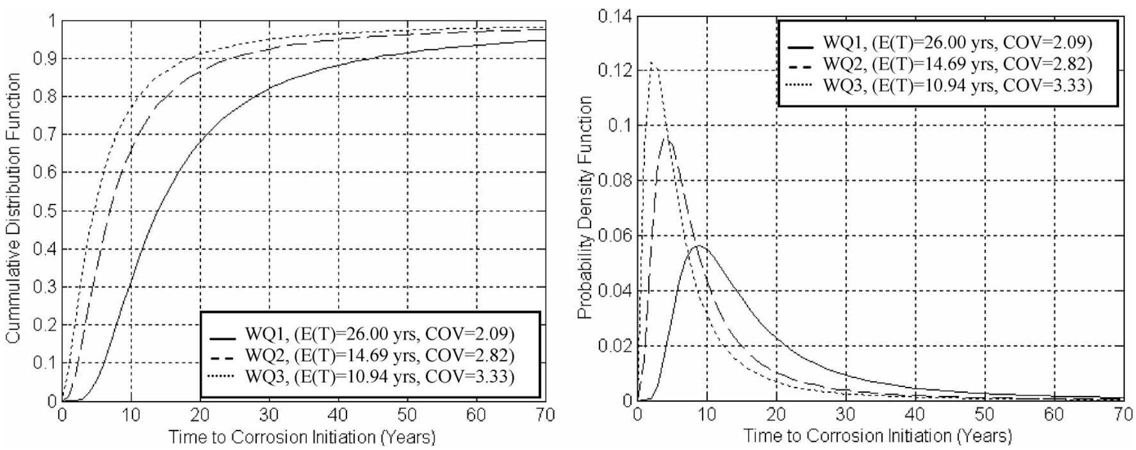

Figure 13. Prior corrosion initiation time for different models of D and X_c.

approximately 35%) at reinforcement level). The posterior time to corrosion initiation at reinforcement level for different models of concrete and workmanship quality and for various sensor initiation times is shown in figure 14. The increase or decrease in mean value of time to corrosion initiation depends strongly on the initiation time at sensor location as can be seen from figure 14, but as can be seen, there is a considerable reduction in uncertainty of posterior performance for all hypothesised sensor initiation times. The reduction in COV is about 70% regardless of concrete quality and sensor initiation time.

Figure 15 summarises the effects of the number of sensors in reducing the uncertainties associated with predicted performance. The reduction in uncertainty is evident (albeit mild after first updating) showing continual effectiveness of updating methodology in reducing associated uncertainties. In contrast to the previous cases, figure 15 shows that the relative difference in COV of corrosion initiation times among different concrete qualities is practically constant after the first updating.

The time to first intervention, assuming 10% probability of corrosion initiation as the durability limit state, based on the prior performance model is 6.1, 2.4 and 1.1 years, respectively, i.e. difference of 5 years between the good and the poor quality case. This difference (i.e. 5 years between these two cases) is almost the same for the posterior predicted performance even though the uncertainty associated with posterior performance is considerably reduced. This demonstrates that workmanship and material quality have a strong influence on both the prior and the posterior performance prediction (corrosion initiation time) unlike the first two parameters examined in this paper (e.g. exposure condition, threshold chloride concentration). This signifies the importance of obtaining additional information in this respect to improve/update the confidence in material and workmanship quality prior to performance evaluation.

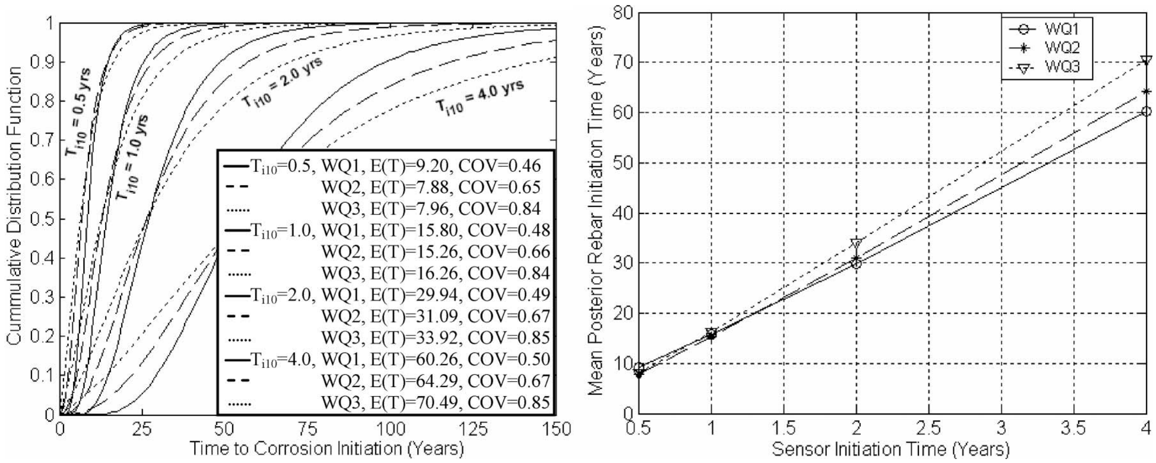

Figure 14. Posterior corrosion initiation time for various models of concrete and workmanship quality and for various sensor initiation times.

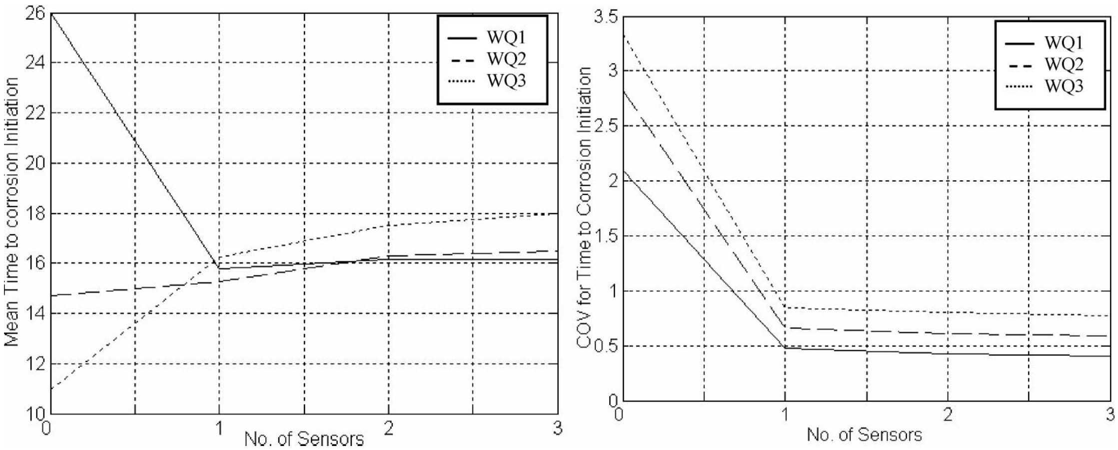

Figure 15. Effects of number of sensors on the updated corrosion initiation time.

4.5 *Instrument/measurement uncertainty*

The instrument/measurement uncertainty affects only the posterior predicted corrosion initiation time. This effect is summarised in figure 16 for different T_{int} models. It can be seen from the figure that for all the three cases of T_{int}, the mean as well as the COV for the posterior predicted corrosion initiation time are practically the same, i.e. the predicted performance is insensitive to the instrument/ measurement uncertainty. This of course is true for the range of T_{int} values selected for this analysis.

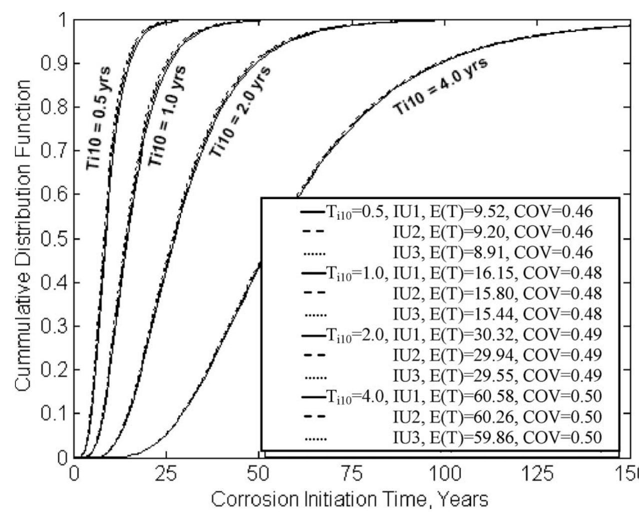

Figure 16. Posterior corrosion initiation time for various instrument/measurement uncertainties.

5. Conclusions

The results of the case study highlight the effects of various uncertainties on the prior as well as posterior predicted performance. It can be concluded from the above results that the uncertainties associated with input parameters significantly affect prior performance distributions whereas posterior performance (time to corrosion initiation in this case) distributions were found to be significantly less sensitive to these input uncertainties, i.e. exposure conditions, threshold chloride concentrations and instrument uncertainties. Hence, the introduction of monitoring together with a methodology for performance updating would be highly beneficial in reducing uncertainties in the management of concrete structures.

A linear correlation between the sensor initiation time at certain depth and the mean posterior rebar corrosion initiation time is evident whereas the COVs for the posterior distributions are insensitive to sensor initiation times. Hence, in the practical applications, the posterior corrosion initiation time at rebar level can be estimated directly from these curves once the actual corrosion initiation time at the sensor location becomes available.

The study of effects of various threshold chloride concentration and exposure condition models on the predicted performance also concludes that updating of overall performance would be more beneficial than monitoring and updating of these parameters on an individual basis.

A comparison of various models for diffusion coefficient and concrete cover shows strong influence of workmanship and material quality on both the prior and posterior performance distributions, thus highlighting the importance of these parameters in predicting structural performance with better confidence. Similarly, the comparison of outcomes from various deterioration model uncertainty distributions clearly demonstrates the need for better predictive models (with lower modelling uncertainty) to improve the confidence in performance prediction, and hence on decisions regarding management of the structures.

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