PROACTIVE HEALTH MONITORING IN PERFORMANCE UPDATING OF DETERIORATING SYSTEMS

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ABSTRACT
Predicting the future condition and safety of deteriorating systems for a foreseeable part of the remaining service life is vital for their effective management. The qualitative information provided by visual inspections is not sufficient for this purpose. The data provided by NDE is quantitative but is intermittent in the time and space. Health monitoring systems using state-of-art instruments have the ability to provide information on the systems behaviour in a continuous, or almost continuous, time scale but can provide information at a few specified locations. All these methods cannot be used explicitly for the prediction of future performance of the systems. On the other hand, research on different materials in the area of performance prediction has led to the development of a range of predictive models for different conditions. The applications of these models are limited due to high level of uncertainties associated with them. The confidence in the predicted performance can be increased by the effective use of information (both qualitative and quantitative) obtained via a range of inspections, testing and monitoring carried out at various stages in the service life of systems. This would enable a more reliable prediction of the condition and safety of the systems; hence provide a tool for their effective management and optimum use of resources.

This paper outlines a methodology for performance updating of deteriorating systems monitored through proactive techniques. The methodology is illustrated using a concrete bridge element prone to chloride induced deterioration, whereby uncertainties associated with time to corrosion initiation are reduced by the effective integration of monitoring data. The extent of deterioration varies considerably at different locations due to its spatial and temporal effects. The use of multiple sensors at various locations would be useful in this context. These can also be used to increase the redundancy of the monitoring system at critical areas. This paper also highlights the advantages and limitations of the updating procedures for the two mentioned scenarios with a view to predicting the performance of the entire monitored domain with increased confidence.

KEYWORDS
Structural Health Monitoring, Performance Updating, Concrete Structures, Systems Performance.

INTRODUCTION

Visual inspections are used to aid maintenance management for almost all deteriorating systems. Despite obvious benefits of being simple, cheap (immediate cost) and that 100% of the systems surface can be checked; these are intermittent, subjective, applicable only to exposed surfaces, and access to the vicinity is mandatory that may involve disruption to the normal operation of the systems. The extent of damage cannot be estimated only by a surface examination; the signs of deterioration may not appear at the surface until it has caused severe internal damage, especially if the defect is not at, or close to, the surface. Furthermore, visual examinations can only provide qualitative information regarding condition of the systems that may not relate explicitly to their safety.

Non-destructive examination (NDE) has addressed several drawbacks of the visual techniques and gained popularity among the maintenance and management communities. The need to be in close vicinity of the area to be inspected is a major hurdle in its use for several applications, e.g. bridges where it becomes costly primarily due to the indirect costs of bridge closure and traffic management. The 'direct' and 'indirect' data provided by NDE is useful because it can be related explicitly to the systems safety but it is generally intermittent in the time and space. Recent innovations in the field of sensing and measurement technology have lead to the development of state-of-the-art monitoring instruments. These health monitoring systems (HMS) have the ability to provide real time information on the behaviour and deterioration characteristics of the systems in a continuous, or almost continuous, time scale. These do not need access to the systems however they can only be applied at few predefined locations.

Prediction of the future condition and performance of deteriorating systems at element or system level for a foreseeable part of the remaining service life is vital for their effective management and intelligent use of scarce resources. Due to the highlighted limitations, the information obtained through visual inspections, NDE and HMS cannot be used explicitly for performance prediction purposes. Furthermore, instrument and measurement uncertainties and the uncertainties in the future performances hinder their direct use for the performance predictions in future. On the other hand, research on different materials, e.g. concrete, steel, and masonry, in the area of performance prediction has lead to the development of predictive models for a range of conditions and to a varying degree of complexity. Uncertainties associated with the nature and rate of deterioration, the demand (past, present and future) and the actual performance of these systems are considerable, and subject to change during their service life. These can be treated formally using probabilistic methods, hence an increasing shift towards probabilistic deterioration modelling is eminent. The input parameters of these models, however, are fraught with uncertainties that limit their effective use to short or medium range predictions.

A powerful decision-support tool may be developed by combining information obtained through structural health monitoring with probabilistic prediction models. This would increase confidence in the predicted performance by reducing associated areas of uncertainties in the probabilistic models. Uncertainties associated with the health monitoring systems can also be incorporated within such a framework to obtain realistic performance predictions.

ISSUES AND LIMITATIONS OF HEALTH MONITORING SYSTEMS

Despite all the advantages offered by the health monitoring systems, there are several issues that should be addressed to facilitate the effective use of instruments for health monitoring of systems. With regard to the spatial variability of deterioration processes, a major concern in the use of HMS is that they only provide information at a small number of specific locations; careful thought has to be given as to how these results can be considered as representative (or not) for the element or entire system.

Another vital issue with the use of HMS is that pertaining to results that are unexpected or might be misinterpreted. If, for example, several sensors are installed at various locations in a system what should the conclusion be, if a sensor contradicts another similar closely located sensor? Alternatively, what if a sensor close to a known defect indicates a less severe condition and another at some distance away indicates a worse condition. Other possibilities of cases that may need to be considered include no readings or clearly erroneous readings obtained from a particular sensor. But even when the sensors are free from obvious errors how confident should we be regarding their output, and to what extent can this information be used for performance prediction purposes?

The above arguments lead to the belief that, instead of relying entirely on the information obtained through location specific monitoring systems, this information should be combined with the prior information regarding the deterioration phenomenon and its prediction through empirical and/or semi-empirical models. This information is often diverse in quality and quantity and certainly contains uncertainty! Thus, a primary objective of combining prior information with monitoring data should be to reduce areas of uncertainties, whilst realising that there are different and diverse sources.

CONTINUOUS AND DISCRETE OUTPUT

The frequency of measurements required on a system depends primarily on the phenomenon being monitored, e.g. the frequency of information obtained through sensors should be very high for live load measurements on a structure to avoid any important reading being missed out. On the other hand, if the phenomenon being monitored is the corrosion of a concrete structure, the sensors output need not be very frequent because of the slow nature of the process. Even though the process of health monitoring may be continuous in nature, the output from the sensors could either be of a continuous or a discrete form depending on the parameters being monitored and the type of sensors being used [1]. Consider, for example, a concrete structure subjected to chloride induced deterioration. Monitoring the chloride concentration at certain depths of concrete cover would yield an output that is continuous in nature. On the other hand, monitoring the threshold chlorides penetration in the cover concrete would be an example of discrete output, in which case the sensor may yield either 'passive state' or 'active corrosion state' at the sensor location.

PERFORMANCE UPDATING

A powerful and versatile approach dealing with probabilistic evaluation and prediction of systems performance is the Bayesian approach. These techniques have had a significant impact in nuclear plants assessment and in the 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 [2-8]. However these applications have focused on very specific deterioration mechanisms and inspection methods delivering 'hard' data, e.g. crack size in fatigue analysis of steel structures. The Bayesian updating approach can be used to incorporate information obtained from different sources at different points-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.

Let the probability distribution for the 'prior time to failure' is $F'_T(t) = P[T(X = X_i) \le t]$. It represents the probability that the 'time to failure' at a given location X_i, $T(X=X_i)$, is less than or equal to any given time, t. Assuming, for simplicity, that the sensor output is discrete; two updating scenarios are possible. The first scenario is the case when the health monitoring system confirms that the predefined limit state has not been attained at the sensor location (confirmation of 'safety') at a particular point in time (i.e. at the time of monitoring, t_m); the 'actual time to failure', T_i, of the sensor (located at X_i) is not known but is greater than the time of monitoring, i.e. $T_i > t_m$.

When the health monitoring system confirms the attainment of a limit state at the sensor location (confirmation of 'failure') at a given time (i.e. second updating scenario), the 'time of failure' at the sensor location would be equal to the time of attainment of the limit state, i.e. $T_i = t_m$. In order to account for the instrument / measurement uncertainty, assuming that the sensor is not perfect. Instead of yielding the 'exact time to failure' at the sensor location, two limiting values for the 'time to failure' are obtained and it can be assumed with reasonable accuracy that below the lower time limit the failure has not occurred, and above the upper limit the failure has occurred. This can mathematically be expressed as 'T_i

$\leq t_m$ and $T_i > t_m - t_{ins}$', i.e. a sensor confirms the attainment of limit state at the time t_m whereas it would have not attained the limit state at the time t_m-t_{ins}. Here the time interval t_{ins} would reflect the uncertainty in instrument and measurement method used. Higher value of the time, t_{ins}, would reflect higher instrument / measurement uncertainty and would reduce the confidence in the posterior predicted performance and vice versa.

Combining the two scenarios and using Bayesian event updating framework, the posterior distribution for the 'time to failure' for a total of 'n' no. of sensors would become [9];

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

Where $F''_T(t)$ = posterior cumulative distribution function for the 'time to failure'.
X_i = location of sensor no. i
$T(X = X_i)$ = priori predicted 'time to failure' at location X_i.
$M(X_i)$ = safety margin for expected 'time to failure' at X_i at a given time t_m.
= $T(X = X_i) - t_m$, when 'safety' is confirmed at location X_i.
= $T(X = X_i) - (T_i - t_{ins})$ when 'failure' is confirmed at location X_i and the 'time to failure' of sensor i, T_i, becomes known.
M_i = Safety margin between predicted and actual 'time to failure', when the 'time to failure' of sensor i becomes known.
= $T(X = X_i) - T_i$ and
= 0 for the 'safety' confirmation case.
T_i = time at which 'failure' is detected by the sensor i.
t_{ins} = time interval between the two events i.e. 'confirmation of failure' and 'confirmation of safety' that reflects the inability of monitoring instruments to detect exact corrosion initiation time.

SYSTEM UPDATING APPROACH

An inherent assumption in the above methodology is that there is only need to consider one location at which both prior and posterior (i.e. using monitored data) distributions are considered. In practice, the extent of deterioration varies considerably from one location to another. These variations can be attributed to the temporal and spatial effects of different variables involved in the deterioration process, within the element and/or for different elements of a system or a network etc. The actual performance in such cases could be different for different elements of a system and even at different locations of the same element. In order to explore the application of the Bayesian methodology in cases where spatial influences are dominant, it is assumed that the monitored domain can be subdivided into a number of smaller zones with the possibility of installing sensors within each zone. The distance between the sensors, and hence the physical size of the zone, should be large enough to avoid any spatial correlation on sensor outputs. On the other hand, the zone should be small enough to justify the assumption of uniform performance over its entire physical size. Another scenario where multiple sensors may be required is, when more confidence in performance prediction is required at some critical location or more robust / redundant monitoring system is required because of the critical nature of the zone. Of course, the two cases could also exist in combination, as shown schematically in Figure 1.

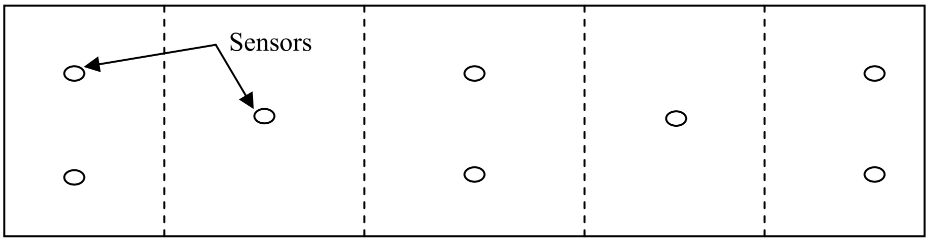

Figure 1 : A structural member divided into five zones.

Performance updating through sensors in different zones

Consider a system divided into a number of small zones and a sensor located in each zone. The outcome of health monitoring in this case would be the 'actual time to failure' at certain depth of each zone. The difference between 'times to failure' at certain depth in each of these zones could reflect the spatial variation of deterioration phenomenon. In this case, the 'time to failure' at sensor location, T_i in Eq. 1, becomes a random variable, which can be represented by either a fitted distribution e.g. normal distribution, or an empirical distribution using the data obtained from multiple sensors located along the space. The posterior 'time to failure' of the system, $F_T^{''sys}$, (composed of different zones) is given by the following equation [Rafiq et al., 2005].

$$F_T^{''sys}(t) = \int F_T^{''zone}(t \mid x = T_i) f_{T_i}(x) dx \qquad \text{Eq. 2}$$

Where $F_T^{''zone}$ is the distribution for the 'time to failure' for each zone given that the actual 'time to failure' obtained through sensor located at X_i is T_i, and $f_{T_i}(x)$ is the distribution for actual 'time to failure' of the zones. The above equation is similar to the expression for the mean value of a function. Hence, the output using this procedure (time to failure for the entire system) is the same as that of weighted average of the predicted performance for the individual zones.

Performance updating through sensors in the same zone

In this case the objective is to either increase robustness of health monitoring instruments or to increase the confidence in prediction depending upon the critical nature of the zone under consideration. Hence, the sensors would be located relatively close to each other (within the same zone) and the assumption is that the deterioration would be uniform within that zone. Bayesian updating can thus be applied for multiple sensors to improve confidence regarding prediction of performance of the zone under consideration. Let 'i' represents the sensor number along the first dimension and 'j' represents the sensor number along the second dimension within a zone then the expression for updating (Eq. 1) using multiple sensor data would become [10]

$$F_T^{''}(t) = P\left(\frac{\left(T_I(X = X_{c,j}) \le t\right) \bigcap_{i=1,j=1}^{ni,nj} M_{i,j} \le 0 \ \bigcap_{i=1,j=1}^{ni,nj} M\left(X_{i,j}\right) > 0}{\bigcap_{i=1,j=1}^{ni,nj} M_{i,j} \le 0 \ \bigcap_{i=1,j=1}^{n,nj} M\left(X_{i,j}\right) > 0} \right) \qquad \text{Eq. 3}$$

Where $T_I(X = X_{i,j})$ = a priori predicted initiation time at location '$X_{i,j}$'; $X_{i,j}$ = location of sensor i,j; n_i = total number of sensors along the first dimension; n_j = total number of sensors along the second dimension; $M(x_{i,j})$ = safety margin for expected 'time to failure' at location '$X_{i,j}$' at any given time 't_m' and is given by '$T(X = X_{i,j}) - t_m$' if 'safety' is confirmed at the sensor location '$X_{i,j}$', and would be '$T(X = X_{i,j}) - (T_{i,j} - t_{ins})$' if the 'failure' is confirmed at location '$X_{i,j}$' and the 'time to failure' at the sensor location, '$T_{i,j}$', becomes available; $M_{i,j}$ = safety margin between predicted and actual 'time to failure', when the 'time to failure' of sensor i,j becomes available and is given by '$T(X = X_{i,j}) - T_{i,j}$' and is equal to '0' for 'safety' confirmation case.

CASE STUDY

In order to show the effectiveness of the updating methodology and to quantify the gain in confidence regarding the predicted performance, a reinforced concrete bridge element prone to chloride induced deterioration is considered. Deterioration of such a system is divided into two main phases; initiation and propagation [11]. Both limit states have been extensively used in literature for the performance prediction. The time for the propagation of chloride induced deterioration since initiation until more severe limit states are attained, i.e. cracking, bond failure or ultimate limit states, etc, is relatively small compared to the time for the initiation of deterioration process [12]. Furthermore, the cost of repair and rehabilitation of the structures in the propagation stage is significantly higher than the repair and maintenance cost during the initiation phase. This paper focuses on a pro-active approach, hence only the initiation phase of the chloride induced deterioration is considered in this example to demonstrate the effectiveness of the health monitoring systems in gaining confidence in performance prediction. A typical model for the time to corrosion initiation based on Fick's second law of diffusion is presented in Eq. 4.

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

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. Due to uncertainties in the quantification of these parameters, probabilistic approach for deterioration modelling is generally adopted, e.g. Thoft-Christensen [13], resulting in a distribution for the corrosion initiation time as shown in Figure 2. 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 (absissa). 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 normalised by the total area. In this case, the target (or threshold) would represent the maximum corrosion damage tolerated for any particular member or structure.

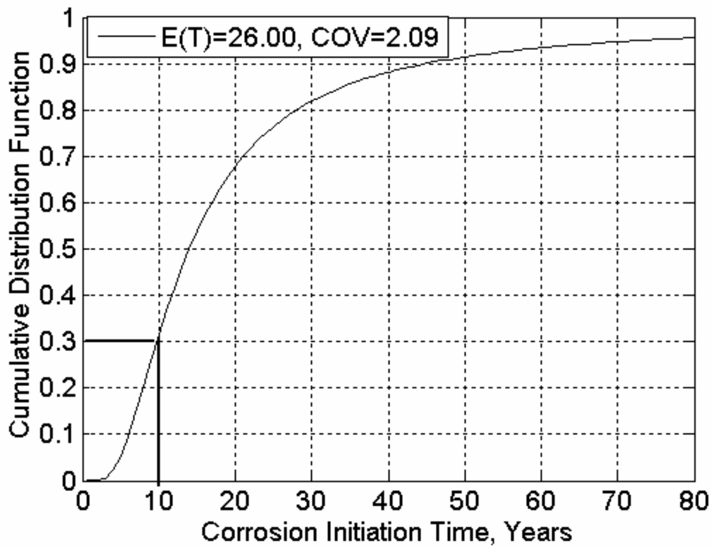

Figure 2: Distribution for the corrosion initiation time.

Monitoring for Corrosion Initiation Phase

Consider now a case where a health monitoring system has been installed to the structure to monitor corrosion risk at various depths below the concrete surface. The instruments available for the corrosion risk measurement include [14];

- Ladder Arrangement
- Metallic Nail System
- Expansion Ring System.

The ladder arrangement (Fig. 3a) can be installed in new structures or during repair works in existing structures. Expansion ring (Fig. 3b) 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. The initiation of corrosion of these steel pieces gives an indication of the corrosion penetration depth into the cover concrete.

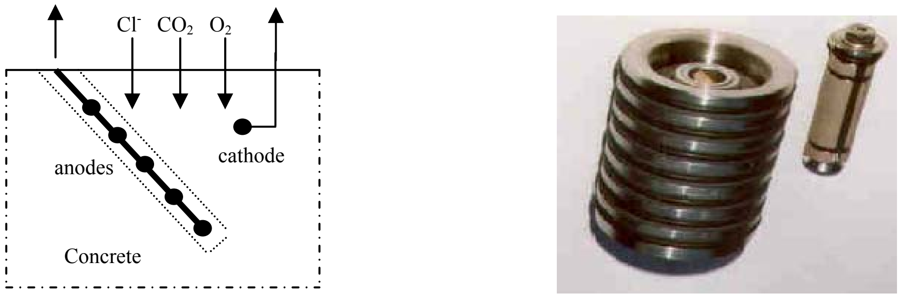

Figure 3: Sensors for corrosion risk monitoring a) Ladder arrangement b) Expansion Ring

The reduction in uncertainty can be quantified by comparing prior and posterior distributions for the time to corrosion initiation for the sensor initiation ('failure' confirmation) or simply confirmation of passivity at sensor locations ('safety' confirmation) as shown in Fig. 4a and 4b respectively. The different assumed times may be attributed to variation in exposure conditions and material properties, etc. It can be seen from these figures that;

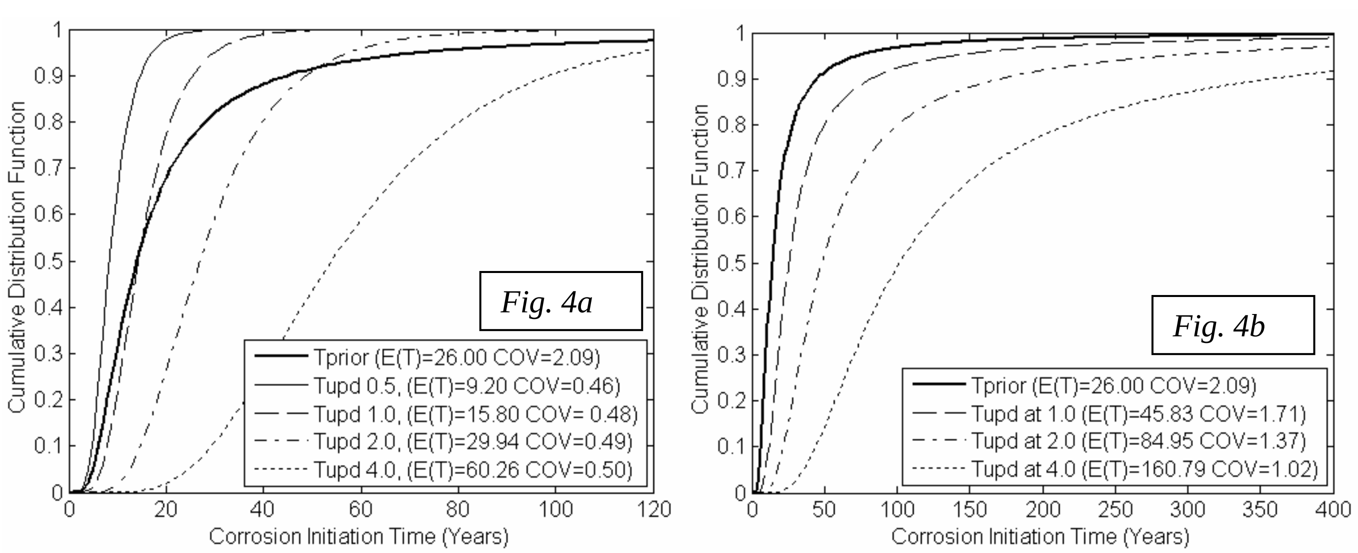

Figure 4: Posterior corrosion initiation time at rebar level
a) Initiation confirmation case b) Passivity confirmation case

- 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. The reduction in uncertainty (in terms of the COV) is more pronounced when the actual time to initiation at sensor location becomes available rather than when only passivity is confirmed at any specific point in time.

- 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. 4a). In the case of confirmation of passivity, the COV reduces continuously with time and approaches 50% after about 4 years (Fig. 4b).
- The change in updated corrosion initiation time at the rebar level (from its prior value) depends upon the early or delayed sensor initiation time from its prior expected value e.g. the mean value of the updated time to corrosion initiation at rebar level reduces (from the prior value of 26.0 years) to 15.8 years if the sensor detects initiation at 1 year time, or increases to 29.94 years for sensor initiation time of 2.0 years (Fig. 4a).

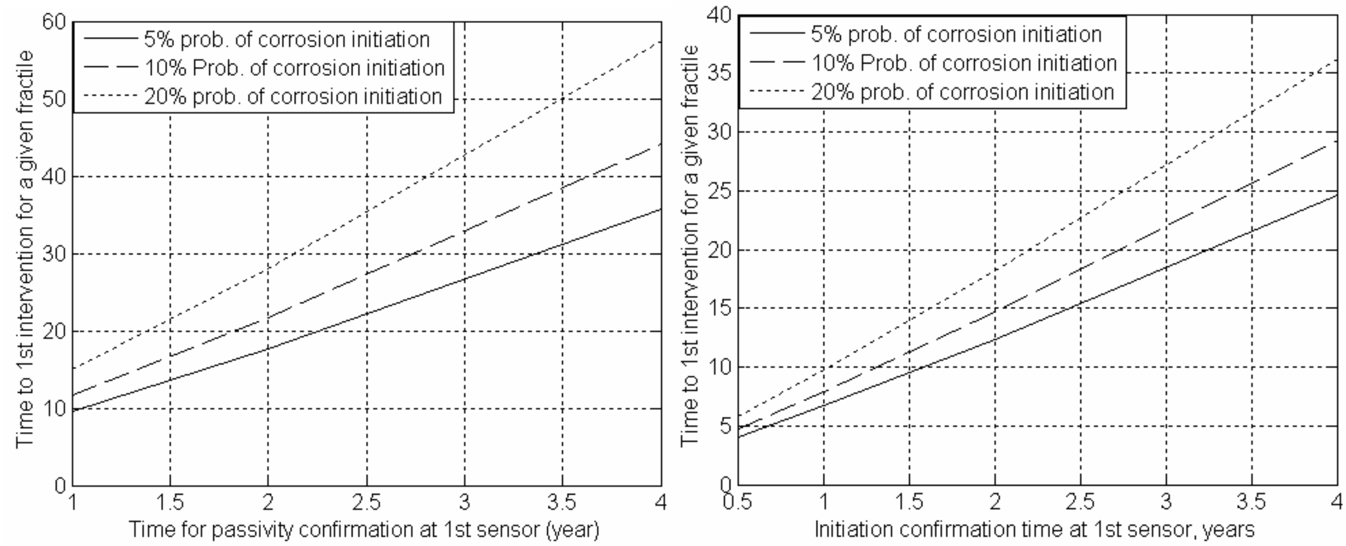

Figure 5: Time to corrosion initiation (at rebar level) for different probability of corrosion initiation and initiation detection times (one sensor at 10mm depth)

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. 5. 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). The results are clearly different for different distribution fractiles (i.e. 10%, 20% etc), and for different scenarios. 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.

Performance updating through sensors in different zones

The posterior predicted performance (corrosion initiation times) assuming five sensors (at 10mm cover depth) distributed along the plan (i.e. a member divided into five zones) is shown in Figure 6. The scenario examined is that the number of sensors at 10mm depth indicating corrosion initiation at 1.0 years varies from zero to five. It is clear from the figure that if all the sensors show the same output i.e. either corrosion initiation or passivity confirmation at a given point in time, the uncertainty associated with predicted performance is considerably less than the case where even one sensor shows diverse results. This reduced level of uncertainty (COV for the posterior performance prediction) in the former case is due to the fact that there are no dominating spatial effects in the system (as reflected by the same output from all the sensors).

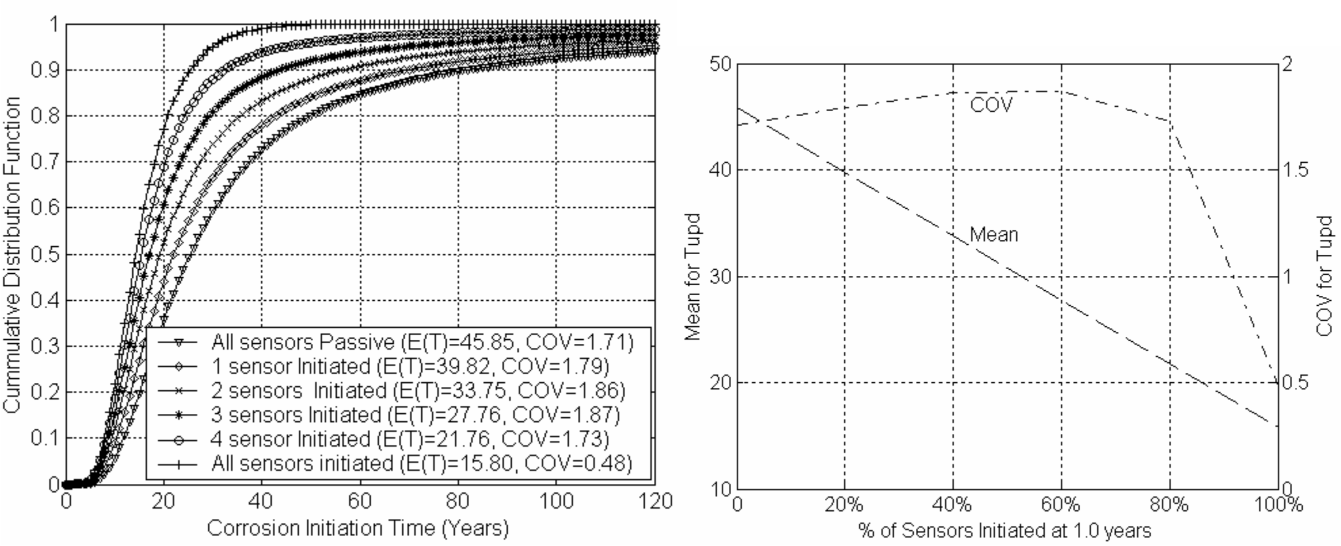

Figure 6 : Corrosion initiation time at rebar level for different percentage of sensors showing initiation.

It can also be seen from the figure that uncertainty levels for the case when all sensors show corrosion initiation (COV = 0.48 in Fig. 6) is considerably less than the case when passivity is confirmed at the sensors (COV = 1.71). This is because the quality of information available with the initiation confirmation case is higher (i.e. the time to corrosion initiation at the sensor location becomes available) than the passivity confirmation case (i.e. the time to corrosion initiation at the sensor location is larger than the time of monitoring, but is still an unknown quantity).

Performance updating through sensors in the same zone

The results (posterior rebar corrosion initiation time) assuming one, two or three sensors in the same zone are shown in Figure 7. The updating is carried out at 1.0 year, assuming all the three sensors are confirming passivity at that point in time. It is clear from the figure that increasing the number of sensors in the same zone would increase the confidence regarding the prediction of performance (as COV for the corrosion initiation time is reducing continuously).

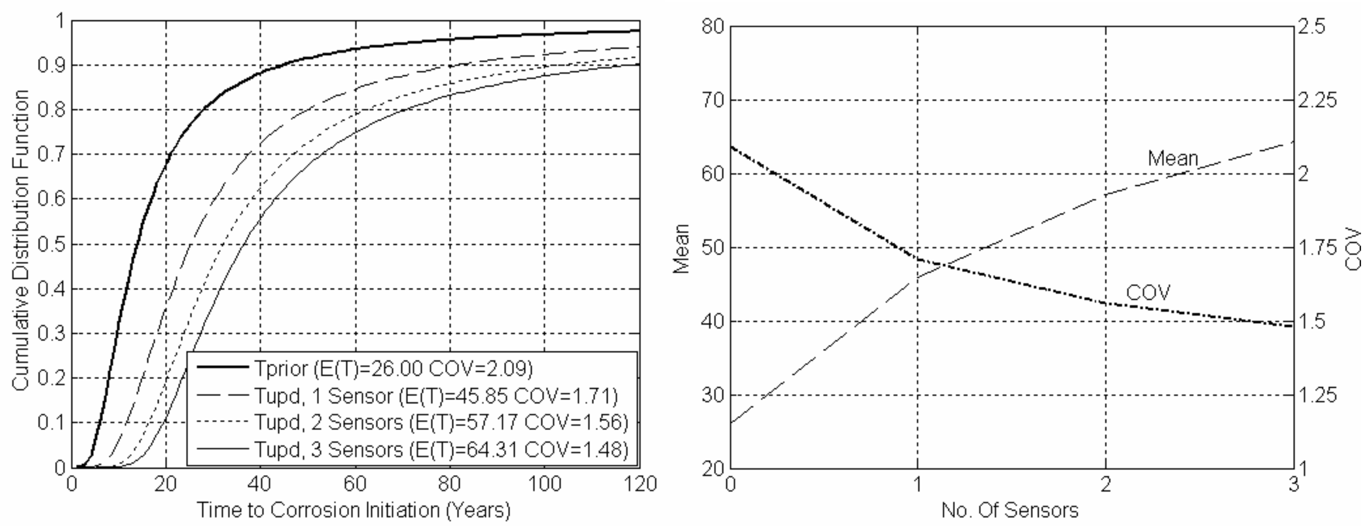

Figure 7 : Bayesian updating for multiple sensors in the same zone showing Passivity Confirmation.

CONCLUSION

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. The extent of deterioration varies at different locations of the system due to temporal and spatial effects of the deterioration. The use of multiple sensors is presented for the above case and for the case where increased confidence in the systems performance is required at critical locations, or increased robustness of the HMS is required. It has been shown that the proposed methodology is applicable for these scenarios and that the overall performance of the element / system can be obtained by rationally combining similar data obtained through sensors at different locations. Further development in this area is required to enable their use for practical applications e.g. methods of dealing with reliability of sensors, and of the information thus obtained, 'best' sensor location, optimum number of sensors required and their distribution, application of these integration methodologies in system analysis tools and management systems, etc. These methodologies should also be tested using field trials before they can be applied confidently for real applications. These issues are being addressed, and will be presented in the near future.

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