Predictive SHM-Supported Deterioration Modelling of Reinforced Concrete Bridges

M.I. Rafiq, M.K. Chryssanthopoulos & T. Onoufriou
School of Engineering, University of Surrey, Guildford, Surrey, UK.

ABSTRACT: The potential benefits of improving performance prediction through the integration of health monitoring systems with probabilistic predictive models, and their implications on the management of deterioration prone structures are presented in this paper. It is shown using case studies that the confidence in predicted performance can be considerably improved through the use of health monitoring methods and hence, the timing of management activities such as inspections, repair and maintenance can be refined to maintain target safety or condition. A comparison of various models for the input parameters indicate that their effects on the performance prediction of deteriorating structures can be minimised through the additional information gained through in-service health monitoring systems. It is also concluded for the scenarios considered that the life-cycle costs (LCC) for the management activities are considerably reduced when the decision support system is aided by structural health monitoring (SHM).

1 INTRODUCTION

In the UK, Highways Agency is administering over 9,000 trunk road and motorway bridges that are valued at over £20 billion. More than 65% of those are either reinforced or prestressed concrete bridges (Mahut & Woodward, 2005). These structures represent 2% of the national network length but 30% of its total asset value. In most developed countries with already established, but aging, infrastructure, the investment on maintenance of these structures is either approaching, or has already exceeded, the capital spent for new construction. In the UK, 50% of the total bridge and large culvert stock were constructed between 1960 and 1980 (Allison & Woodward, 2005). The UK's Highways Agency has a maintenance program of £7 billion from 2001 to 2010 for their administered transport network (Highways Agency, 2005). The effective maintenance management of high value assets such as bridges is of increasing importance and significant research is directed towards this area.

In general, deterioration of concrete structures is associated with the corrosion of reinforcement embedded in concrete (Gaal et al., 2001). This is caused mainly by either carbonation or chloride attack. These mechanisms are unique in the sense that the aggressive agents penetrate into the concrete without any visual signs of deterioration until they reach the reinforcement level and initiate corrosion. In addition to the loss of section in the steel bars, the expansive products of corrosion cause delamination and spalling of concrete, which ultimately may lead to failure of the structure. Chloride ions have been found to be a major factor contributing towards deterioration in reinforced concrete structures (Gaal et al., 2001).

2 PREDICTIVE MODELLING AND LIMITATIONS

Generally aggressive agents penetrate from outside sources, e.g., the amount of chloride cast into concrete is limited by design codes, but the problem starts as chloride ions ingress from outside. Whatever the source (de-icing salts, marine environment), the ingress is a complex phenomenon and involves different transport processes, e.g. initial penetration, absorption and capillary suction, and diffusion. The deterioration processes in concrete have been modeled using a variety of approaches, e.g. based on Fick's 2nd law of diffusion (Collipardi et al., 1970), based on Markov chain process (Cesare et al. 1992), using Neural network models (Elkordy et al., 1993), modified solution of Fick's law assuming a fixed amount of surface contents (Frangopol, 1997), modeling diffusion using Nernst-Einstein equation (Chatterji, 1994), experimental data of cracked concrete (Li, 2002), diffusion as a combination of Kundson and Viscous flow (Li et al., 2003). 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 modeling 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 modeling process. Uncertainty in the variables involved in the deterioration process is generally modeled using random variables. Spatial variability of the deterioration process and lack of knowledge regarding its details also contributes towards the complexity in modeling deterioration and associated uncertainty (e.g. Stewart et al. 2004). 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).

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

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. Due to uncertainties in the quantification of these parameters, probabilistic approach for deterioration modeling is generally adopted, e.g. Thoft-Christensen et al. 1996, resulting in a distribution for the corrosion initiation time as shown in Fig. 1. The parameter values were obtained from published sources and are detailed in Rafiq, 2005.

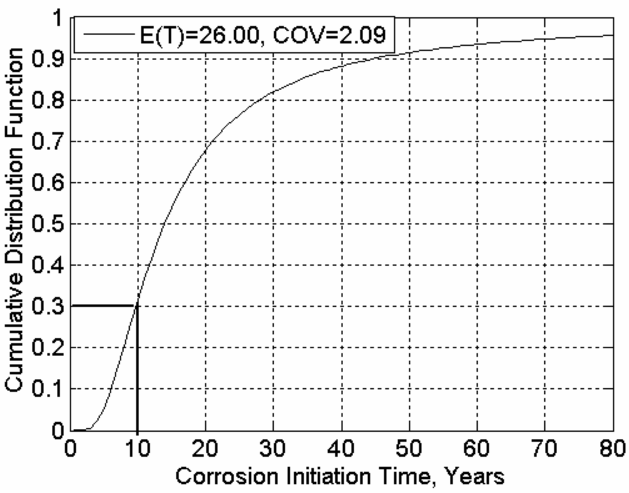

Figure 1: Distribution for the corrosion initiation time.

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.

3 SHM-SUPPORTED PREDICTIVE MODELLING

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 modeling and those associated with the use of SHM (highlighted in Sec. 2 and above) can be considerably reduced by combining the two effectively. A framework has been proposed by the authors which combines the information obtained from SHM with predictive deterioration modeling to improve the confidence in the predicted performance (Rafiq, 2005). The key elements and benefits from the approach are discussed below.

4 PERFORMANCE UPDATING

An important element of the proposed framework is updating which is a powerful and versatile approach in dealing with probabilistic evaluation and prediction of systems performance. This technique has 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 optimization of inspection and maintenance schedules (e.g. Onoufriou, 1994; Estes and Frangopol, 1999 and Righiniotis, 2004). 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.

4.1 *Performance Updating with information through single sensor*

In the present application, Bayesian updating is used to incorporate the information obtained from corrosion sensors. For simplicity, it is assumed that the sensor output is discrete. Two scenarios are possible in this case. 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 cover depth, 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.

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 (Rafiq et al. 2004);

$$F_T^{"}(t) = P\left[\frac{[T_I(X = X_c) \leq t] \bigcap_{i=1}^{n}[M_i \leq 0] \bigcap_{i=1}^{n}[M(X_i) > 0]}{\bigcap_{i=1}^{n}[M_i \leq 0] \bigcap_{i=1}^{n}[M(X_i) > 0]}\right] \qquad \text{Eq. 2}$$

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.

The prior and posterior (updated) distributions for corrosion initiation time at the rebar level (assumed at 40mm cover depth), given the sensor at 10mm cover depth indicates initiation confirmation at different times (taken as 0.5 years to 4.0 years), are plotted in Fig. 2a. Similarly the distributions for the rebar corrosion initiation times when the sensor confirms 'passivity' at different times (taken as 1.0, 2.0 and 4.0 years) are plotted in Fig. 2b.

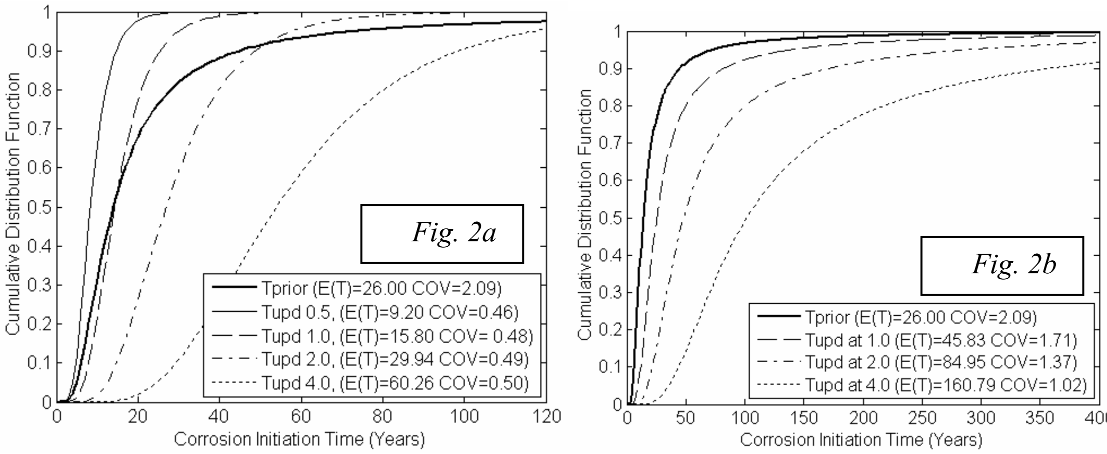

Figure 2: Posterior corrosion initiation time at rebar level. a) Initiation confirmation b) Passivity confirmation

It can be seen from Fig. 2 that uncertainty is reduced with the availability of additional information (both 'passivity' or 'initiation' confirmation) which is represented by the reduction in coefficient of variation (COV) in the posterior distribution compared to the prior. Also it is evident that the reduction in uncertainty level is dependent on the quality of information obtained through health monitoring. Confirmation of 'initiation' yields a tighter distribution because the actual time to initiation of the sensor becomes available which is not the case in 'passivity' confirmation where the only available information is that the corrosion initiation time is greater than the time of monitoring.

4.2 *Performance Updating with information through multiple sensors*

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 prior 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 3.

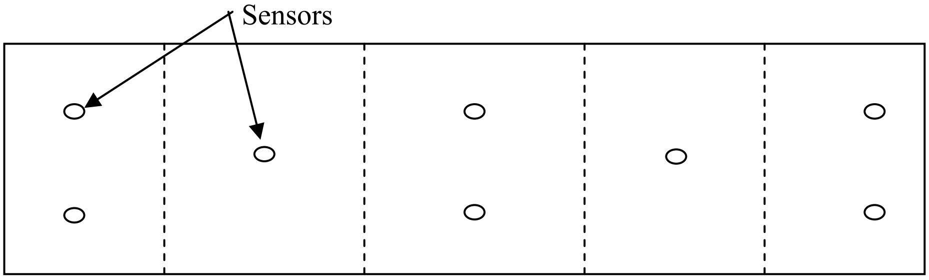

Figure 3 : A structural member divided into five zones.

The details of the updating methodologies for the two cases can be found in Rafiq et al. (2005a). The posterior predicted performance (corrosion initiation time distributions) assuming five sensors (at 10mm cover depth) distributed along the plan (i.e. a member divided into five zones) is shown in Fig. 4 whereas the posterior predicted performance assuming 1, 2 and 3 sensors installed within the same zone is plotted in Fig. 5.

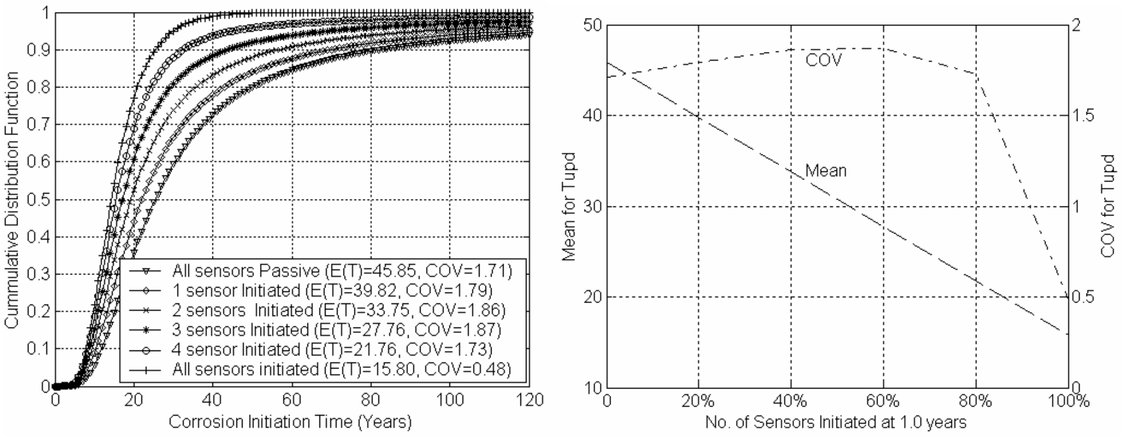

Figure 4 : Corrosion initiation time at rebar level for different no. of sensors showing initiation (at 10mm depth).

The scenario examined in Fig. 4 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 5 highlights the benefit that can be obtained from increasing the number of sensor within the same zone. The updating in Fig. 5 is carried out at 1.0 year assuming all three sensors confirm ‘passivity’. Other multiple sensor scenarios were also examined which are available in Rafiq et al. (2005a). The increase or decrease in the mean value for the corrosion initiation time is dependent on the sensor initiation time. However, it is clear that increasing the number of sensors would increase the confidence regarding the prediction of performance as the COV for the corrosion initiation time is reducing continuously.

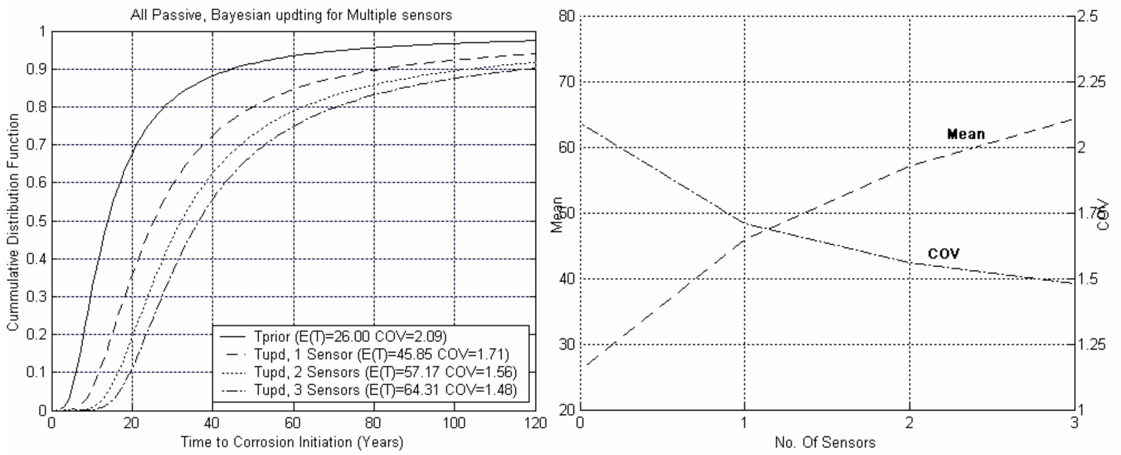

Figure 5 : Effects of Bayesian updating for multiple sensors in the same zone showing Passivity Confirmation.

5 SENSITIVITY ANALYSIS

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 et al. (2006).

Two distinct types of behavior 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. 6, which refer to different assumptions for the model uncertainty distribution, the posterior COV reduces for various input models whereas for the results shown in Fig. 7, which refer to different assumptions regarding exposure conditions, the posterior COV for various input models reduces and converges to a single value. It has also been concluded from this study that the posterior performance prediction is considerably less sensitive to variations in the input parameters when compared to the prior predictions which is one of the benefits of the proposed approach.

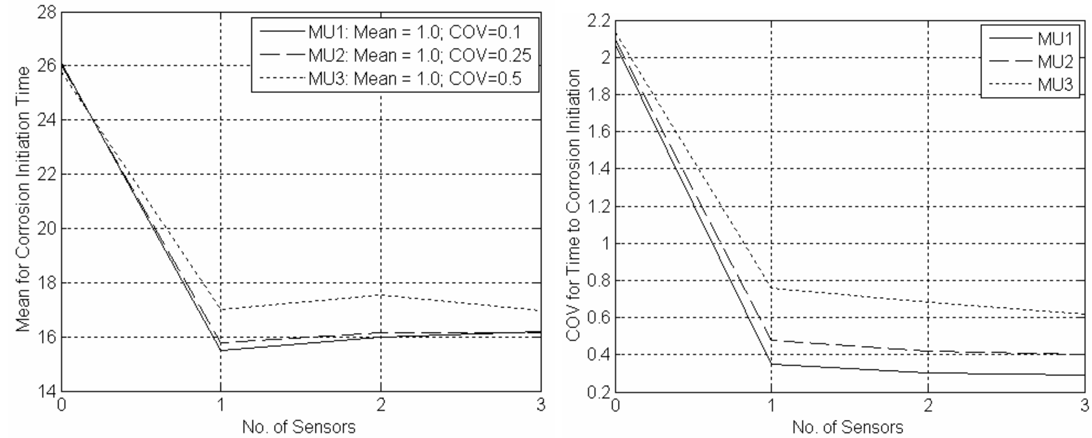

Figure 6: Effect of number of sensors in reducing uncertainty for time to corrosion initiation.

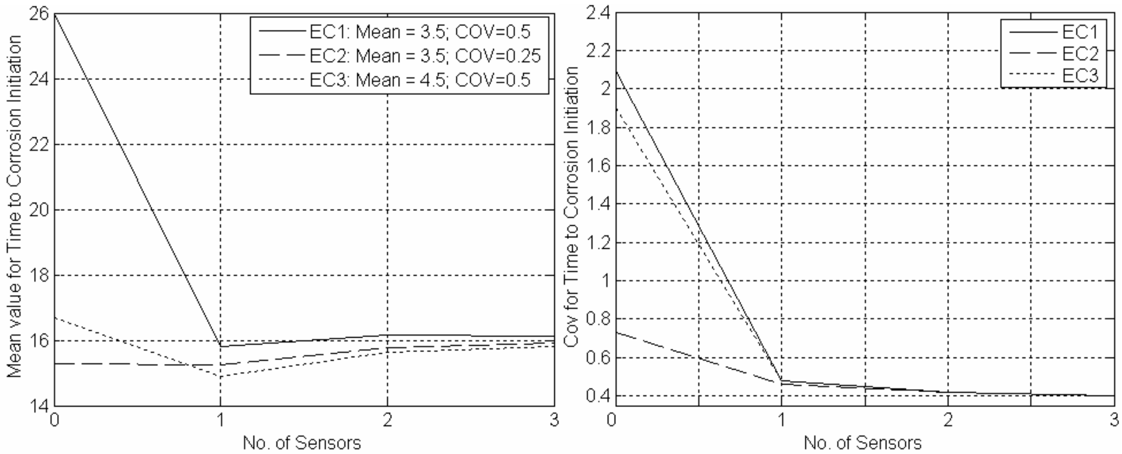

Figure 7: Effects of no. of sensors on uncertainty associated with exposure conditions.

6 LIFE-CYCLE COST ANALYSIS

As highlighted in the previous sections, the increase in confidence can provide justification for the delay in major intervention activities (i.e. detailed inspections and/or major repair activity). To demonstrate the effects of such delays in the major interventions on the life-cycle costs (LCC) and the effects of SHM-supported predictive models on the decision support system, a comparison of four management strategies is carried out using life-cycle cost analysis. A system (consisting of four members) subjected to chloride induced deterioration is assumed and using hypothesized inspection results and compatible data for SHM. The management strategies compared in this study are;

Strategy A: Decisions based only on regular inspections.
Strategy B: Decisions based on predictive models supported through regular inspections.
Strategy C: Decisions based on predictive models supported through optimized inspection.
Strategy D: Decisions based on predictive models supported through SHM.

The details regarding this analysis are available in (Rafiq et al., 2005b and Rafiq, 2005). The results obtained for these strategies are summarized in Figure 8. The costs considered in this study are the direct costs related to inspections and repairs only. It is recognized that indirect costs (e.g. traffic management and user delays, etc) may have a significant influence in the results.

The figure clearly indicates that strategy A has the least costs under the particular hypothesized inspection outcomes considered. However, it is not possible to maintain a target performance level, and hence the probability of failure would be higher compared to the other cases where a target performance level is maintained throughout the service life. This example highlights the inability of current practice of regular inspections to maintain consistent performance levels in structures.

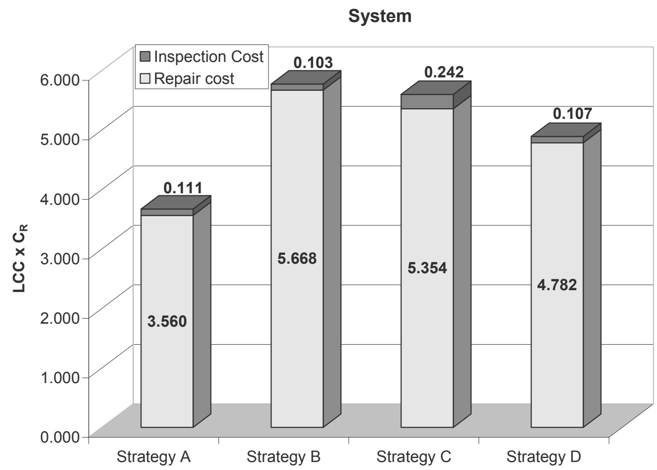

Figure 8 : Life cycle cost comparison for the members and the overall system

Among strategies B, C, and D where a target performance level is maintained throughout, strategy D is generally the most economic. Figure 8 also demonstrates that the cost of repair is the major factor contributing towards the life cycle costs. The inspection and monitoring cost is small compared to the repair costs for the ratios examined herein (C_R/C_I=75, C_M/C_I=2). The results for other C_M/C_I ratios examined are available in Rafiq (2005).

7 CONCLUSIONS

Predicting future condition and reliability of the deteriorating structures is vital for their effective management. As the input parameters of the deterioration models developed to serve the purpose are uncertain, this limits their use of these models for long range predictions. On the other hand, state-of-the-art health monitoring systems have been developed to obtain structure specific information regarding deterioration characteristics and loading etc. The potential benefits of improving performance prediction through the integration of health monitoring systems with probabilistic predictive models, and their implications on the management of deterioration prone structures are presented in this paper through the development of an integrated methodology. It is shown, through application case studies, that the confidence in predicted performance can be significantly increased through the use of SHM-supported modeling of deterioration and the major inspection and maintenance activities can be delayed on the account of increased confidence in the predicted performance. A sensitivity study of various input parameters on the predicted performance concluded that the effects of different input models are considerably reduced through the developed updating methodology. A life-cycle cost analysis for various management strategies (with and without the use of SHM) highlighted the safety and cost benefits that can be obtained through the use of SHM-supported predictive models. Clearly more work is needed in this area including field data collection to reduce the uncertainties associated with some of the assumptions made.

REFERENCES

Allison, B. and Woodward, R.J. 2005. Inspection, testing, and monitoring of trunk road bridges in England. In G.A.R. Parke & P. Disney (eds), Bridge Management 5: 171-178 .London: Thomas Telford.

Cesare, M., Santamarina, J., Turkstra, C. and Vanmarcke, E. 1992. Modelling bridge deterioration with Markov Chains. Journal of Transportation Engineering, ASCE, 118(6): 820-833.

Chatterji, S. 1994. Transportation of ions through cement based materials, part 1 : fundamental equations and basic measurement techniques, Cement and Concrete Research, 24: 907-912.

Collipardi, M., Marcialis, A. and Turriziani, R. 1970. The kinetics of penetration of chloride ions in concrete. II Cemento, No. 4:157-64.

Duracrete 1998. Modelling of degradation. Duracrete, Probabilistic performance based durability design of concrete structures. European Union-Brite EuRam III, BE95-1347, Dec. 1998.

Elkordy, M.F., Chang, K.C. and Lee, G.C. 1993. Neural networks training by analytically simulated damaged states. Journal of Computing in Civil Engineering, 7 (2): 130-145.

Estes, A.C. and Frangopol, D.M. 1999. Repair optimization of highway bridges using system reliability approach. Journal of Structural Engineering, July 1999: 766-775.

Frangopol, D.M. 1997. Application of life-cycle reliability-based criteria to bridge assessment and design. In P.C. Das (eds), Safety of Bridges: 151-157, London: Thomas Telford.

Gaal, G.C.M., Veen, C.V.D. and Djorai, M.H. 2001. Deterioration of concrete bridge in the Netherlands. In: Forde, M.C. (eds), Structural Faults and Repairs. Edinburgh: Engineering Technics Press.

HETEK (1996). Chloride penetration into concrete. State of the art. Report no. 53. The Danish Road Directorate.

Highways Agency 2005. Strategic Roads 2010: Highways Agency 10 years national Road Strategy. www.highways.gov.uk. London: Highways Agency UK.

Li, Q.S., Zheng, J.J. and Shao, L. 2003. A new solution for the prediction of chloride ingress in reinforced concrete flexure members. ACI Material Journal, 100 (4): 319-325.

Li, C.Q. 2002. Initiation of chloride-induced reinforcement corrosion in concrete structural members – prediction. ACI Structural Journal, March/April 2002: 133-141.

Mahut, B. and Woodward, R.J. 2005. Comparison of bridge management practice in England and France. In G.A.R. Parke & P. Disney (eds), Bridge Management 5: 163-170 .London: Thomas Telford.

Onoufriou, A., Fowler, D. and Smith, J.K. 1994. Reliability based optimization inspection planning. In Proc. of the 7th Intl. Conf. on Behaviour of Offshore Structures, Boston.

Rafiq, M.I., Chryssanthopoulos, M.K. and Onoufriou, T. 2006. Sensitivity of uncertainties in performance prediction of deteriorating concrete structures. Structure and Infrastructure Engineering, In Press.

Rafiq, M.I. (2005) Health monitoring in proactive reliability management of deteriorating concrete bridges. PhD Thesis, School of Engineering, University of Surrey, UK.

Rafiq, M.I., Chryssanthopoulos, M.K. and Onoufriou, T. 2005a. The role of proactive health monitoring in performance prediction: A systems approach. ICOSSAR’05, CD-Rom Proceedings.

Rafiq, M.I., Chryssanthopoulos, M.K. and Onoufriou, T. 2005b. Comparison of different management strategies using life-cycle cost analysis of bridges. In G.A.R. Parke & P. Disney (eds), Bridge Management 5: 578-586. London: Thomas Telford.

Rafiq, M.I., Chryssanthopoulos, M.K. and Onoufriou, T. 2004. Performance updating of concrete bridges using proactive health monitoring methods. Reliability Engineering and System Safety, Vol. 86: 247-256.

Righiniotis, T.D., 2004. Influence of management actions on fatigue reliability of a welded joint. International Journal of Fatigue, Vol. 26: 231-239.

Stewart, M.G., Faber, M.H. and Gehlen, C. 2004. Temporal ans spatial aspects of probabilistic corrosion models. In Frangopol, D.M., Bruhwiler, E., Faber, M.H. and Adey, B. (eds), Life-cycle performance of deteriorating structures, Assessment, design and management : 183-193. ASCE, USA.

Stewart, M.G. and Rosowsky, D.V. 1998. Time-dependent reliability of deteriorating reinforced concrete bridge decks. Structural Safety, Vol. 20: 91-109.

Thoft-Christensen, P., Jensen, F.M., Middleton, C.R. and Blackmore, A. 1996. Assessment of the reliability of concrete slab bridges. In D.M. Frangopol, R.B. Corotis, R. Rackwitz (eds), 7th IFIP WG 7.5 Working Conf. on Reliability & Optimization of Structural Systems: pp 321-328.