

# Life-cycle performance of structures: combining expert judgment and results of inspection

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**ABSTRACT:** Current bridge management systems base decisions on the results of visual inspections. These systems consider visual inspection results as accurate and disregard any further information available. In the present study, the result of each inspection is considered as a random variable, dependent of a wide range of factors, that can be integrated with other sources of information, including expert judgment and results of other inspections. The combination of different sources of information results in reliable posterior information and allows more accurate predictions of future deterioration. In the present paper, performance of an existing structure is obtained in terms of the condition index, which describes the effects of deterioration as can be seen by an inspector, and the safety index, which measures the safety margin of the structure. The reduction in uncertainty associated with periodical inspections is considered through updating of performance profiles. The updating of the condition index is direct, as new information on this parameter is collected by the inspector. In terms of safety, however, only indirect information is collected and the uncertainty reduction associated with an inspection is significantly lower. Several realistic examples show the impact of inspections on the predicted life-cycle performance of structures.

## 1 INTRODUCTION

Inspections of existing structures are a fundamental aspect of every structural management system. In fact, structural deterioration depends on such a wide range of factors, that direct observation must be considered the prime source of accurate and reliable information on the structure.

Inspections are not, however, free of errors and uncertainty (Phares *et al.* 2004). In fact, the result of an inspection depends on several factors such as the experience of the inspector, the deterioration mechanisms present, location of the bridge, and means available for the inspection. Moreover, the results of inspections alone do not allow a medium or long term planning, and any decisions based on the results of inspections alone will result in application of maintenance to very deteriorated structures, resulting in a very high life-cycle maintenance costs (Neves, Frangopol and Cruz 2006; Neves, Frangopol and Petcherdchoo 2006).

For these reasons, it is fundamental to integrate the results of inspection with a prediction model for the deterioration of existing civil infrastructure. In this manner, more accurate predictions of future deterioration will be possible, and more efficient decisions can be made.

In this paper, the deterioration of existing structures is analyzed considering the model developed by the authors (Neves and Frangopol 2005). In this model, the performance of structures is defined in terms of lifetime probabilistic condition, safety, and cost profiles. The main advantages of this model are the ability to consider the entire performance history of the structure, including deterioration and effects of maintenance actions as well as the ability to combine common performance indicators, namely the condition index, with more consistent indicators, such as the safety index.

The model proposed by the authors (Neves and Frangopol 2005) does not include any information resulting from inspections or tests in the analysis, as it bases the evolution over time of performance on expert judgment alone.

In this paper, a model for combining expert judgment in the form of the model proposed by Neves and Frangopol (2005) with information from inspections is proposed. This new approach is based on the use of Bayesian updating combined with simulation for improving expert judgment. The results obtained in the examples analyzed show the significant impact on performance prediction of the inclusion of information obtained from inspections.

## 2 CONDITION, SAFETY AND COST

In the model proposed by Neves and Frangopol (2005) life-cycle performance of an existing structure is characterized by three different time-dependent probabilistic indicators: condition index, safety index, and the cumulative maintenance cost. The condition index is an indicator of deterioration as recorded by a bridge inspector. It might be associated with the severity of cracking in reinforced concrete structures, deterioration of painting and rusting in steel structures, or any other visually observable deterioration effect. The safety index is a measure of the reliability or the safety margin of a structure, and can only result from a structural safety evaluation.

These two indicators are related, in the sense that both refer to the effects of deterioration on a certain structure. However, full knowledge on one of these factors is not enough to determine the value of the other. In fact, the condition index is only influenced by the observable defects, and only indirectly includes the effects of corrosion, fatigue or cracking. The safety index includes all these aspects directly. In short, the safety index would be a much more interesting measure of performance. However, it is extremely expensive to determine the safety margin of a structure, and the network system reliability analysis of all structures in a large network is close to impossible.

In the model proposed by Frangopol (1998) and Neves and Frangopol (2005), the condition and safety indices under no maintenance are defined as bi-linear functions, in terms of 6 random parameters: initial condition,  $C_0$ , initial safety index,  $S_0$ , time of initiation of deterioration of condition and safety,  $t_{ic}$  and  $t_i$ , respectively, and deterioration rate of condition and safety,  $\alpha_c$  and  $\alpha$ , respectively. The effect of maintenance actions is defined in terms of 8 random parameters, as follows: (a) improvement in condition index and safety index immediately after application,  $\gamma_c$  and  $\gamma$ , respectively; (b) time during which the deterioration processes of condition index and safety index are suppressed,  $t_{dc}$  and  $t_d$ , respectively; (c) time during which the deterioration rate in condition index and safety index are suppressed or reduced,  $t_{pdc}$  and  $t_{pd}$ , respectively; and (d) deterioration rate reduction of condition index and safety index,  $\delta_c$  and  $\delta$ , respectively. The meaning of each of these random variables is shown in Figure 1.

The mean, standard deviation, histograms and percentiles of the life-cycle condition index, safety index, and cumulative cost are computed using Monte-Carlo simulation. A detailed description of the computational platform employed can be found Neves and Frangopol (2005).

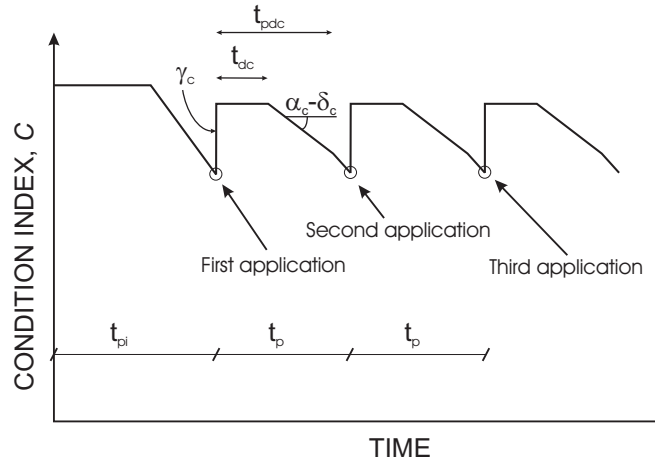


Figure 1. Condition index profile

## 3 CONDITION AND SAFETY UPDATING

When an inspection is executed, new information on the condition index of the structure at a certain point in time becomes available. If the inspection was perfect, it would be possible to know, exactly, the condition index at that point in time. Since the inspection is affected by errors and uncertainty, this new information must be regarded as probabilistic, and must be used as such.

At the time of an inspection, the condition index can be characterized as a probabilistic variable, with a probability density function dependent on the results obtained by the inspector, but also on the quality of the inspection. Common practice defines the results of an inspection in terms of a set of possible outcomes (0, 1, ..., n). However, deterioration has, for most cases, a continuous or almost continuous evolution, and these results are a simplification of reality. We can consider that for a given condition index at time  $T$ ,  $C_T$ , the result of an inspection,  $C_{ins}$ , is given as a likelihood function  $P(C_{ins} | C_T) = L(C_T)$ . This function can be approximated by a normal distribution with mean  $\mu$  and standard deviation  $\sigma$ . The mean will be equal to the result of inspection  $C_{ins}$ , if the results of inspections are unbiased, and lower or higher than  $C_{ins}$ , if inspectors are consistently optimistic or pessimistic, respectively. In this paper, it is assumed that inspections are unbiased and that a lower condition index is associated with a lower deterioration. The uncertainty in the results is measured by the standard deviation  $\sigma$ , which is related to the quality of inspection, dependent on the experience of the inspector and the conditions for inspection.

Based on Bayes theorem, the probability density function of the condition index, considering the result of inspection and the information from expert judgment can be defined as (Ang and Tang 2007):

$$f''(C_T) = K \cdot L(C_T) \cdot f'(C_T) \quad (1)$$

where  $f'(C_T)$  is the probability density function of the condition index at time  $T$  considering both expert judgment and results of inspections, also designated posterior distribution,  $f'(C_T)$  is the probability density function of the condition index at time  $T$  considering only expert judgment, also designated prior distribution  $L(C_T)$  is the likelihood function, and  $K$  is a normalizing constant defined by:

$$K = \frac{1}{\int_{-\infty}^{\infty} L(C_T) \cdot f'(C_T) dC_T} \quad (2)$$

Considering Monte-Carlo simulation was used to computed the probabilistic indicators of performance, the mean and standard deviation of the condition index at time  $\tau$ , can be computed as (Chen and Ibrahim 2000, Frangopol and Neves 2008):

$$\mu_C^\tau = \frac{\sum_{i=1}^n C_\tau^i \cdot L(C_T^i)}{\sum_{i=1}^n L(C_T^i)} \quad (3)$$

$$\sigma_C^\tau = \sqrt{\frac{\sum_{i=1}^n (C_\tau^i)^2 \cdot L(C_T^i)}{\sum_{i=1}^n L(C_T^i)} - \left( \frac{\sum_{i=1}^n C_\tau^i \cdot L(C_T^i)}{\sum_{i=1}^n L(C_T^i)} \right)^2} \quad (4)$$

where  $\mu_C^\tau$  and  $\sigma_C^\tau$  are the mean and standard deviation of the condition index at time  $\tau$  considering both expert judgment and results of inspections,  $C_\tau^i$  is the condition index at time  $\tau$  associated with sample  $i$ ,  $C_T^i$  is the condition index at time of inspection  $T$  associated with sample  $i$ , and  $n$  is the number of samples.

In terms of the safety index, a similar approach can be employed, resulting in a mean and standard deviation given, respectively, as:

$$\mu_S^\tau = \frac{\sum_{i=1}^n S_\tau^i \cdot L(C_T^i)}{\sum_{i=1}^n L(C_T^i)} \quad (5)$$

$$\sigma_S^\tau = \sqrt{\frac{\sum_{i=1}^n (S_\tau^i)^2 \cdot L(C_T^i)}{\sum_{i=1}^n L(C_T^i)} - \left( \frac{\sum_{i=1}^n S_\tau^i \cdot L(C_T^i)}{\sum_{i=1}^n L(C_T^i)} \right)^2} \quad (6)$$

where  $\mu_S^\tau$  and  $\sigma_S^\tau$  are the mean and standard deviation of the safety index at time  $\tau$  considering both expert judgment and results of inspections and  $S_\tau^i$  is the safety index at time  $\tau$  associated with sample  $i$ . In this manner, it is possible to obtain new updated condition and safety profiles. It must be noted that

the inspection only provides direct information on the condition index. If the safety index is considered independent of the condition index, then the prior and posterior safety profiles will coincide. Nevertheless, since both the condition index and safety index depend on the deterioration, some correlation is to be expected, and some information on the safety of the structure can be extracted from an inspection.

## 4 EXAMPLES

As an example, the life-cycle condition and safety profiles of existing reinforced concrete bridge elements are analyzed considering data provided in Denton (2002). This data is thoroughly analyzed in Neves and Frangopol (2005), considering the life-cycle performance under no maintenance and under different maintenance strategies. The condition and safety profiles under no maintenance obtained are presented in Figure 2.

As can be observed from these results, under no maintenance the performance presents very significant dispersion, as denoted by the difference between the values of the 5 and 95 percentiles ( $C_{0.05}$  and  $C_{0.95}$ , respectively).

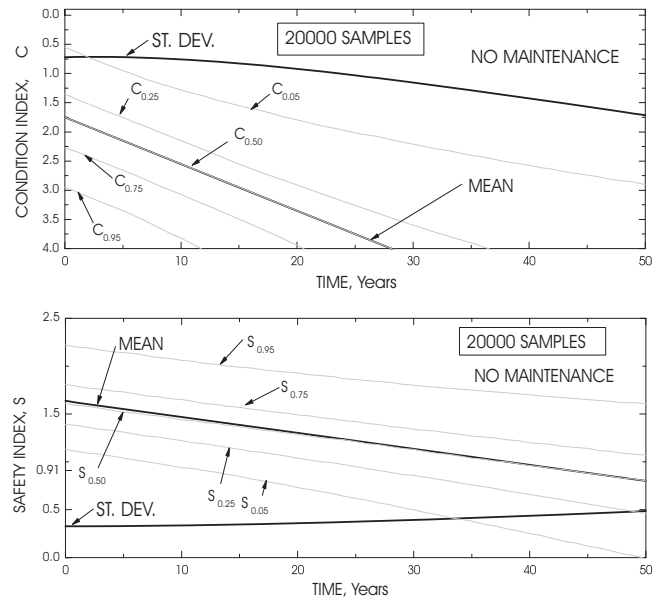


Figure 2. Condition and safety index under no maintenance

Let's now consider that an inspection is carried out at year 20. It is considered that the inspector classifies the bridge element as having a condition index equal to 2, 3, or 4. Considering the experience of the inspector, different levels of quality are defined, each associated with a probability of misclassification. Assuming a normal distribution for the likelihood function, the probability of misclassification is associated with the different standard deviations, as follows (Frangopol and Neves 2008):

Quality	Probability of misclassification	Standard deviation
High	5%	0.255
Medium	10%	0.304
Low	20%	0.390
Very Low	40%	0.595

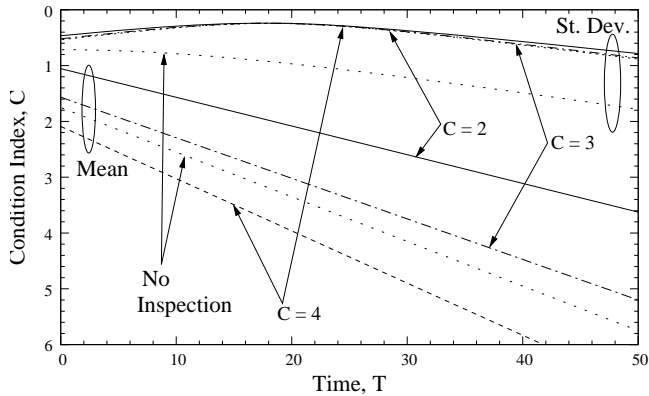


Figure 3. Comparison of the mean and standard deviation of condition index considering only prior knowledge and prior knowledge and inspection

Considering no correlation between the condition index and the safety index, this inspection does not affect the safety index. However, in terms of condition, the updated condition index is significantly different from the profile predicted based on expert judgment as shown in Figure 3, considering a high quality inspection.

These results show that an inspection has a significant impact of the predicted condition index. In fact, for different results of inspection, a significant reduction in the standard deviation of the condition index occurs. Moreover, an important change in the predicted mean condition is also observable. The latter is more dramatic if the observed condition is 2.0, as this is significantly different from the mean predicted value.

In Figures 4 and 5 the PDFs of the condition index considering an inspection with an observed condition index equal to 2 and equal to 3, respectively, are shown.

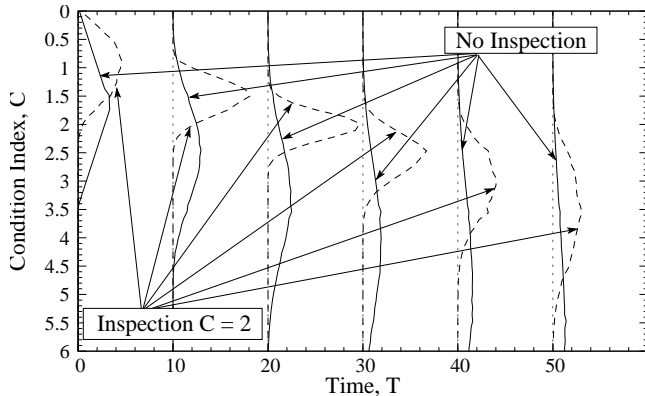


Figure 4. Comparison of the PDFs of the condition index at 10 years time intervals considering only prior knowledge and prior knowledge and inspection,  $C = 2$

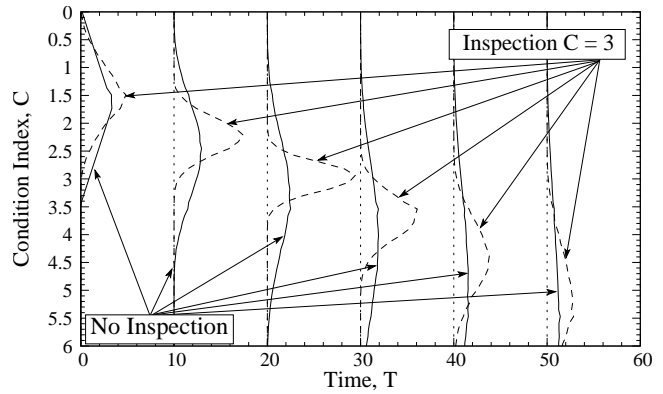


Figure 5. Comparison of the PDFs of the condition index at 10 years time intervals considering only prior knowledge and prior knowledge and inspection,  $C = 3$

These PDFs show the effect of maintenance on the degree of knowledge on the condition of a structure. In fact, for both inspection results, the updated condition PDFs show a reduction in dispersion but also a large shift in the mode. In all cases, there is an important change in the distribution of the initial parameters, namely the initial condition index and the deterioration rate.

#### 4.1 Effect of quality of inspection

An inspection should yield a condition index very close to the real condition of the bridge. This is not the case for two major reasons. Firstly, it is very difficult to the inspector to give a precise indication of the condition, and usual systems use only a limited number of condition classes (*e.g.*, five different classes). As a consequence, even for a perfect inspection a result of 3 means the condition is close to 3.0 (*i.e.*, between 2.5 and 3.5). Moreover, limited experience, difficult accessibility to the structure, or human error also result in errors in the classification of the condition of structures. In the present work, as previously stated, four different types of inspections were considered. A high quality inspection will provide a good indication on the condition of a structure and can be extremely informative. However, the amount of information provided is reduced when the quality of the inspection decreases. Let's consider an example similar to the previous one, but assuming different inspection qualities. The results obtained, assuming that all inspections resulted in a classification of condition index  $C = 2$  are shown in Figure 6.

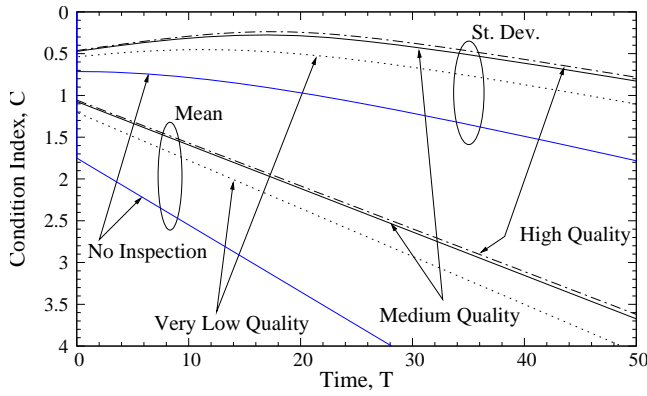


Figure 6. Comparison of the mean and standard deviation of the condition index considering only prior knowledge and prior knowledge and inspection with different quality levels

Figure 6 shows that, even very low quality inspections have a large impact on the condition index profiles, resulting in a reduction in the standard deviation and an increase in mean condition. This is mostly a consequence of the initial data available. In fact, the data presented in Denton (2002) refers to a large set of bridges with very different ages, and not to a single bridge. As the inspection is conducted on a single bridge, the information gathered reduces significantly the uncertainty over present, past and future condition.

#### 4.2 Effect of inspection on the safety index

Although an inspection yields no direct information on the safety index of a structure, this information can be obtained in an indirect manner. In fact, changes in the condition index and the safety index are both the result of deterioration, and, as a consequence, worst condition index is often associated with lower safety.

The probabilistic relation between the condition index and the safety index can be measured by the correlation between these two indicators at any point in time. If no maintenance is considered and the parameters defining the profiles under no maintenance (*i.e.*, the initial condition, initial safety, deterioration rate of condition index and deterioration rate of safety index) are assumed independent, the resulting condition index and safety index will be independent.

If, on the other hand, the parameters defining the condition index and the safety index are correlated, the resulting profiles will also be correlated, and an inspection will improve the knowledge on the condition index, but also on the safety index.

In general, no information on the correlation between parameters defining the condition index and the safety index exists. Let's assume the correlations between these parameters as denoted in Table 1.

In this table, the correlation coefficient between parameters,  $\rho$ , is taken as 0, 0.2, 0.6, and 0.9.

Table 1. Correlation coefficient between parameters defining the condition index and the safety index under no maintenance

	$\alpha_c$	$\alpha$	$C_0$	$S_0$
$\alpha_c$	1	$\rho$	0	0
$\alpha$	$\rho$	1	0	0
$C_0$	0	0	1	$\rho$
$S_0$	0	0	$\rho$	1

In Figure 7 the safety index profiles are obtained considering that an inspection is performed at year 20 and a condition index equal to 2.0 is observed. These results show that, even for relatively low correlation coefficients, there is a significant improvement in mean safety, as a consequence of the observed condition index being better than the initial prediction. Moreover, a reduction in the dispersion of the safety index over the entire lifetime is also observed.

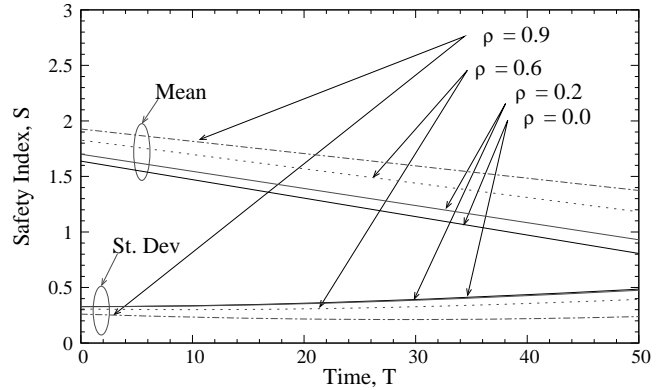


Figure 7. Comparison of the mean and standard deviation of the safety index considering (a) only prior knowledge and (b) prior knowledge and inspection with different correlations

## 5 UPDATE OF INITIAL PARAMETERS

The condition index and safety index profiles are defined in terms of a set of random parameters. When updating is carried out, new information on these parameters becomes available. This information can be used to make more accurate predictions for other structures.

As an example, in Figure 8, the distribution of the deterioration rate of condition considering only expert judgment is compared to the updated distribution. Inspection causes a reduction in uncertainty, but also a reduction in the deterioration rate, as the observed condition is better (*i.e.*, less deteriorated) than initially predicted.

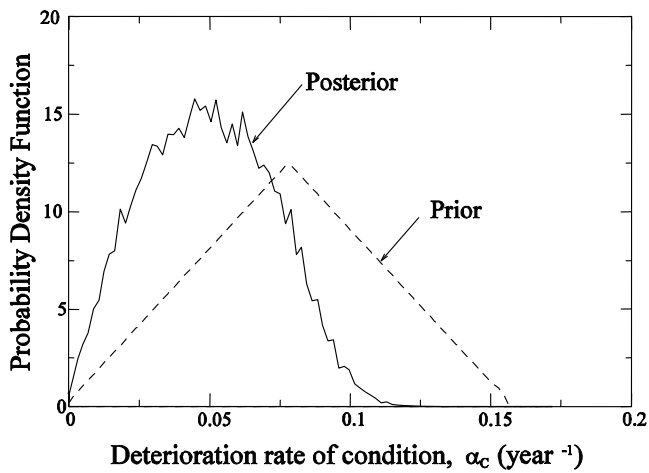


Figure 8. Comparison of the deterioration rate of condition considering only prior knowledge and prior knowledge and inspection

## 6 CONCLUSIONS

In the present study, a methodology to combine expert judgment and results of inspection on the life-cycle prediction of deteriorating structures is proposed. The methodology uses the probabilistic deterioration model proposed by the authors. The effects on this prediction of inspections are defined in a Bayesian framework. The obtained results show that an inspection, even of low quality, results in a significant reduction in uncertainty.

The results obtained show the importance of incorporating the outcome of inspections in the deterioration models in a consistent manner. As a result, more accurate predictions of performance can be obtained, and more sound decisions can be made.

## 7 ACKNOWLEDGMENTS

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