Inspection validation model for life-cycle analysis

J.D. Bakker
Civil Engineering Division, Ministry of Transport, Public Works and Water Management, Utrecht, The Netherlands

J.M. van Noortwijk
HKV Consultants, Lelystad, The Netherlands, and Faculty of Electrical Engineering, Mathematics and Computer Science, Delft University of Technology, Delft, The Netherlands

ABSTRACT: Design decisions lead to future maintenance needs. In the past, these decisions were often taken implicitly. During the last decade there has been a development to make more explicit choices, based on the expected condition in time sometimes combined with life-cycle cost analysis. The inspection validation (IV) model is currently under development. This decision-support model can be used to evaluate the a priori design assumptions on the condition in time versus the actually measured deterioration. The aim of the IV model is to bridge the gab between design and inspection, and to provide maintenance engineers with better founded maintenance advises. The variability of the deterioration in time is modeled by a gamma process. Its parameters have been estimated based on inspection data by combining the methods of least squares and maximum likelihood. Some practical examples of the inspection validation model are discussed.

1 INTRODUCTION

The Netherlands Ministry of Transport, Public Works and Water Management (Rijkswaterstaat) uses several models for optimizing life-cycle costs for critical elements of structures. These models optimize initial investment costs at construction against the future costs of preventive and corrective replacement, as well as the costs of lifetime-extending maintenance. They are used to define general or specific maintenance strategies on element level, or to perform a life-cycle analysis on alternative design solutions. Important input for these optimizations is the deteriorating condition as a function of time including its uncertainty.

Recently the so-called “inspection validation model” has been developed. This decision support model considers both the a priori predicted condition over time and the updated predicted condition based on inspection results. If life-cycle costing models are used in combination with the inspection validation model, then design and inspection procedures can be integrated.

This paper shows how the inspection validation model can be used to evaluate different types of deterioration predictions. The cases that are dealt with in this paper are merely hypothetical and are meant to show how the inspection validation model can be used. Because the inspection validation model is currently in a pilot stage, no application was yet available at the moment this paper was written.

2 NEED FOR LIFE-CYCLE COST OPTIMIZATION TOOLS

In the past decade, there were two developments at Rijkswaterstaat that created the need for life-cycle cost optimization tools. First, each structure that is constructed creates pressure on future available maintenance budgets. Decisions should be made which balance initial investment costs against maintenance costs. Second, for the purpose of infrastructure management each structure that Rijkswaterstaat owns is provided with a maintenance plan (Bakker and Volwerk, 2003). These plans forecast the future maintenance costs on element level, based on nationally or locally defined maintenance strategies, derived from the expected condition in time. These strategies can be justified with life-cycle cost analysis.

3 PREDICTED MAINTENANCE COSTS BASED ON EXPECTED CONDITION

3.1 *Implicit forecasts*

During the design phase of a structure many implicit forecasts are made for the expected future maintenance need. For instance: a concrete bridge is constructed using the national building codes with an expected lifetime of 80 years. The codes will provide boundary conditions on concrete cover and concrete quality. These boundary conditions include implicit durability assumptions ensuring the structure to last for 80 years.

3.2 *Explicit forecasts*

Sometimes maintenance is forecasted explicitly. For instance:

- A steel retaining wall is constructed with a surplus of steel thickness of 2 mm. These 2 mm should be sufficient to make the retaining wall last for 50 years.
- Based on the Reference Documents (Klatter et al., 2002), the forecasted average maintenance intervals for the asphalt pavement on the bridge are:
  - Replacement of the porous asphalt top layer every 10 year
  - Replacement of the total asphalt every 22 year
- Sometimes the required lifetime of concrete structures is defined in construction contracts. Contractors have to prove, for instance by DuraCrete calculations (DuraCrete, 2000ab), that the desired lifetime is reached with a predefined certainty. This implies that the concrete structure is theoretically free of maintenance for the desired lifetime.

3.3 *Forecasts based on life- cycle optimization*

One of the tools used at Rijkswaterstaat is the LEM model (Bakker et al., 1999; van Noortwijk and Frangopol, 2004). This model can optimize intervals of replacement and lifetime-extending maintenance (LEM) based on:

- expected condition in time,
- uncertainty in condition in time,
- costs of preventive replacement,
- costs of corrective replacement,
- costs of lifetime-extending maintenance,
- parameters for the effect of lifetime extension on the condition.

Based on the lowest present value of the life-cycle costs, the model determines optimal intervals of lifetime-extending maintenance and replacement. The LEM model has been applied to optimize the maintenance of the coatings on the steel gates of a Dutch storm-surge barrier (Heutink et al., 2004). In this application, lifetime extension is defined as local spot repair of the coating and replacement as removing the old coating and placing a new one. The condition parameter is the percentage of the corroded surface.

4 EVALUATION OF DETERIORATION PREDICTIONS WITH INSPECTIONS

Predictions of the future condition of civil structures are uncertain. Often, there is not much statistical data available and simulation programs don't take into account all the (mutually dependent) parameters involved. Therefore, inspections are needed to validate the current predictions of the condition over time and to update them (Figure 1). This is not an easy task, since there is not always a clear relation between the predictions and the relevant inspection parameters. The inspection validation model can be a tool to support inspection validation in a uniform manner.

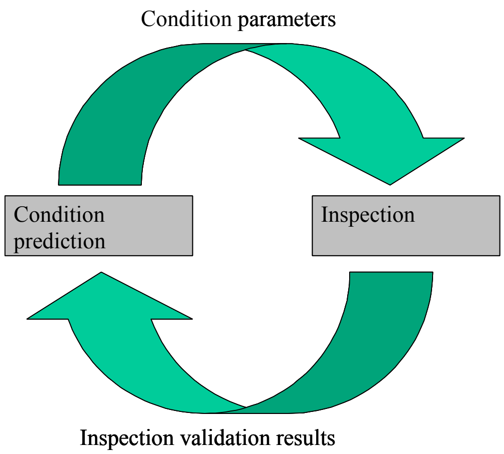

Figure 1. Inspection validation cycle.

5 INSPECTION VALIDATION MODEL

The Inspection Validation (IV) model is a decision-support model. It presents the a priori predicted condition as a function of time versus the updated condition based on inspection results. Based on the updated prediction, the maintenance engineer can decide to:

- Do nothing: wait until the next inspection;
- Change the inspection strategy;
- Change the maintenance strategy;
- Make a life-cycle cost analysis based on the predicted condition.

Figure 2 shows an example of a graphical output. The solid lines represent the a priori predicted time-dependent condition with the 95% confidence interval and the dotted lines represent the updated time-dependent condition based on the inspection results.

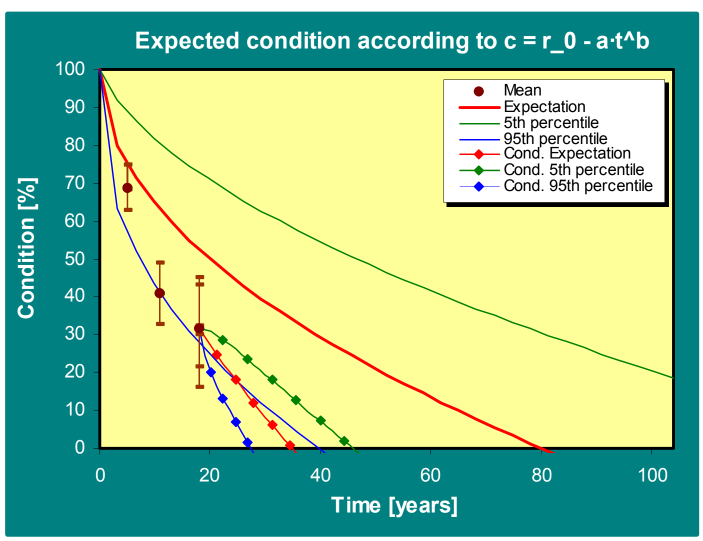

Figure 2. Output example of the inspection validation model with expected average condition in time.

So far, the IV model only deals with variability in time (temporal variability). It is assumed that every inspection assessment (vertical line in the graph) results in a single perfect measured condition (the point at each vertical line). In practice, there are more uncertainties involved than only temporal variability. As shown in the graph, each inspection may result in one or more measured conditions (horizontal short lines that cross the vertical line). This scatter is mainly caused by:

- measurement error due to imperfect inspections,
- spatial variability of material quality and exposure conditions,
- statistical uncertainty due to a lack of data.

To approximately deal with these uncertainties, each inspection validation is done on two levels:

- an inspection validation of the evaluation of the average condition in time,
- an inspection validation of the most deteriorated spot in terms of a representative value.

It is (arbitrarily) assumed that each set of measurements represents a random sample from a normally distributed random variable. The condition of the most deteriorated spot is (also arbitrarily) assumed to be the average condition minus 1.8 times the standard deviation.

6 EXAMPLE 1: INSPECTION VALIDATION BASED ON IMPLICIT PREDICTION

A concrete bridge deck is designed for 80 years, using the common building codes. From practical experience it is known that this will approximately result in a repair of 1% of the concrete surface every 30 years. In other words: some damage is expected over the lifetime due to chloride-induced corrosion and other deterioration mechanisms. Chloride ingress is defined as the critical condition parameter. Without any further knowledge of the structure, this is roughly translated in the following (so far not technically evaluated) inspection parameters:

- At the end of the service life, the average chloride content should not be greater than 0.4% m/m by cement mass (reference value 1);
- At the end of the service life, the local chloride content should not be greater than 1% m/m by cement mass (reference value 2);
- Six chloride measurements should be taken from surfaces that are in direct contact with deicing salts.

The deterioration at a specific time at a specific location is derived from a measured chloride profile. It is defined as follows: “The depth at which the chloride content equals the reference value, divided by the concrete cover times 100%”.

The a priori estimate of the expected condition (or resistance) at time t [in percentage] can be written by the following simplified formula:

$$E(R(t)) = 100 - E(X(t)) = 100 - 21.6 \times t^{0.35}, \quad t \geq 0 .$$

The uncertainty in the deterioration process $X(t)$ is represented by the coefficient of variation (defined as the standard deviation divided by the mean) of the deterioration at the time at which the expected deterioration equals the failure level. This coefficient of variation is 0.2. This leads to the inspection validation on the (hypothetical) average values as shown in Figure 3. The inspection validation of the most-deteriorated areas leads to the result in Figure 4.

Based on the updated predicted condition in time, the maintenance engineer concludes that deterioration in time is faster than expected. The design life of 80 years will most likely not be met without major repair. Therefore a change of inspection and maintenance strategy is needed. Preventive maintenance could be to apply paint on the concrete surface to stop chloride ingress. Alternatively one can wait until corrosion starts and postpone the maintenance as long as possible. As long as no major corrosion is observed, one may well be able to postpone maintenance action for fifteen years. However, repair after fifteen years will be considerably more expensive than preventive maintenance now. Therefore an economic evaluation by means of calculating the present value of the costs of both options should be made.

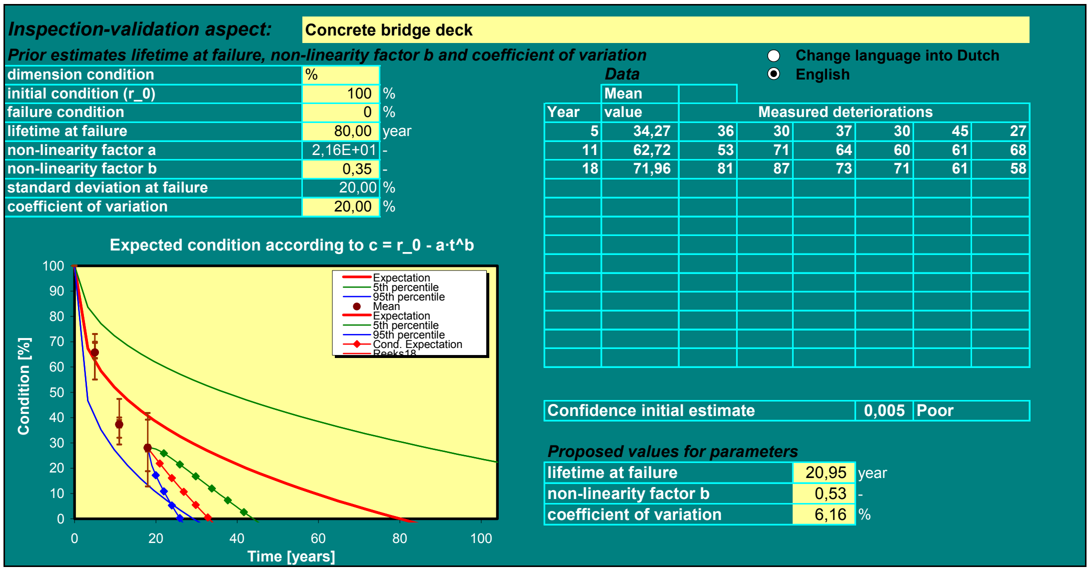

Figure 3. Inspection validation on average values, reference value chloride content = 0.4% m/m.

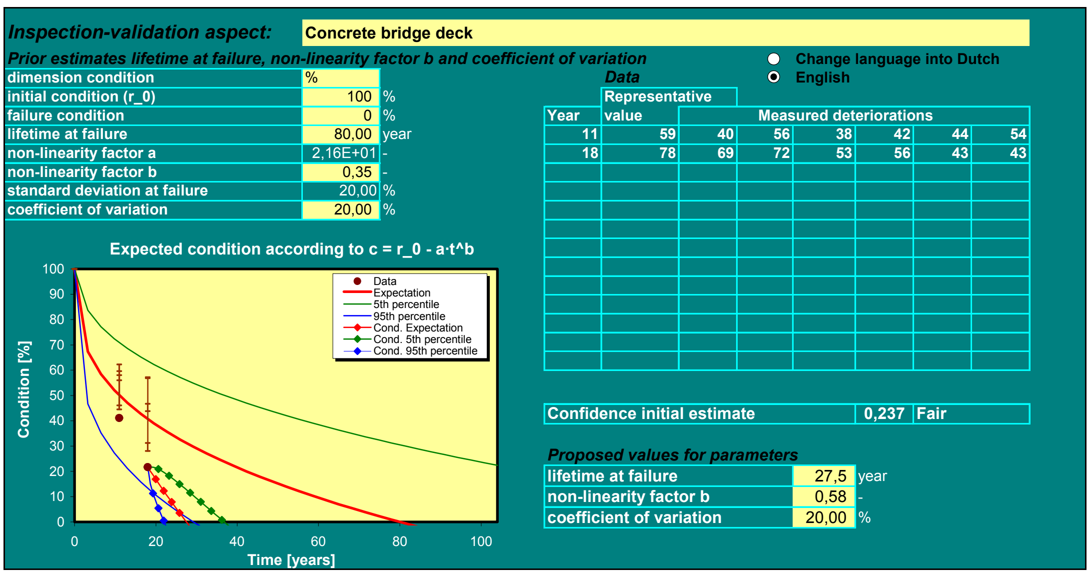

Figure 4. Inspection validation on representative values, reference value chloride content = 1,0 % m/m.

7 EXAMPLE 2: INSPECTION VALIDATION BASED ON EXPLICIT PREDICTION

A steel retaining wall is designed for 50 years. From a structural point of view, the thickness of the retaining wall should be 6 mm. A surplus of steel thickness of 2 mm is applied. Corrosion is defined as the critical condition parameter. Without any further analysis of the local environmental conditions, this is roughly translated in the following (so far not technically evaluated) inspection parameters:

- At the end of the service life, the average steel thickness should not be less than 6 mm (reference value 1);
- At the end of the service life, the local steel thickness should not be less than 4 mm (reference value 2)
- Six thickness measurements should be done on surfaces directly above the waterline.

The deterioration at a specific time at a specific location is defined as: “Measured steel diameter minus the reference value divided by the initial thickness minus the reference value times

100%”. In mathematical terms, the a priori prediction of the condition [in percentage] in time is given by

$$E(R(t)) = 100 - E(X(t)) = 100 - 4.37 \times t^{0.8}, \quad t \geq 0 .$$

The corresponding coefficient of variation is 0.2. This leads to the inspection validation on (hypothetical) average values as shown in Figure 5. The inspection validation of the most-deteriorated areas leads to the result in Figure 6.

Based on the predicted condition, the maintenance engineer concludes that deterioration in time is a little faster than expected for the average criteria. Therefore, he advises to do a more detailed study of the structural consequences of the concrete corrosion, taking into account a limited residual lifetime.

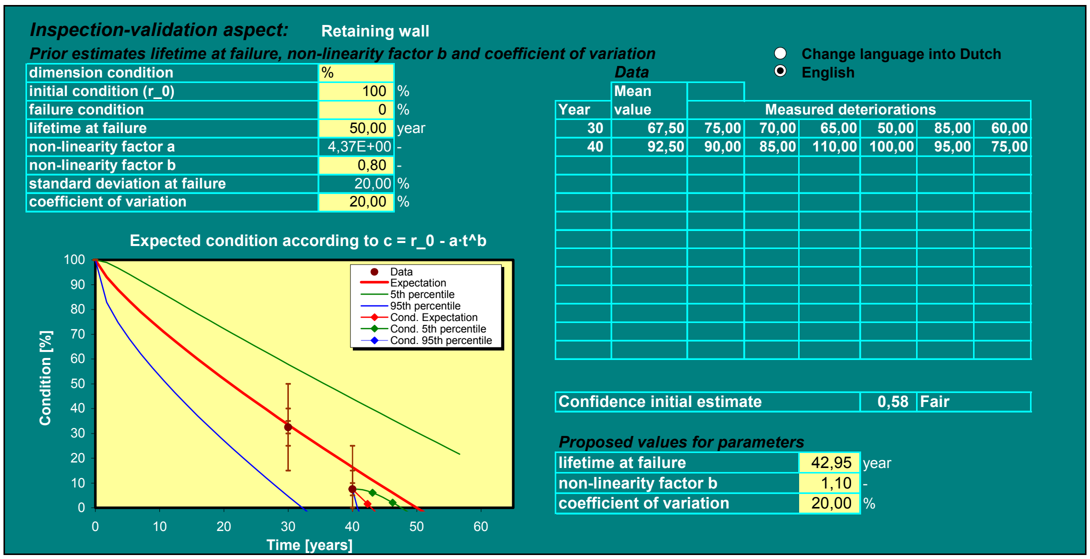

Figure 5. Inspection validation on average values, reference value steel thickness: 6 mm.

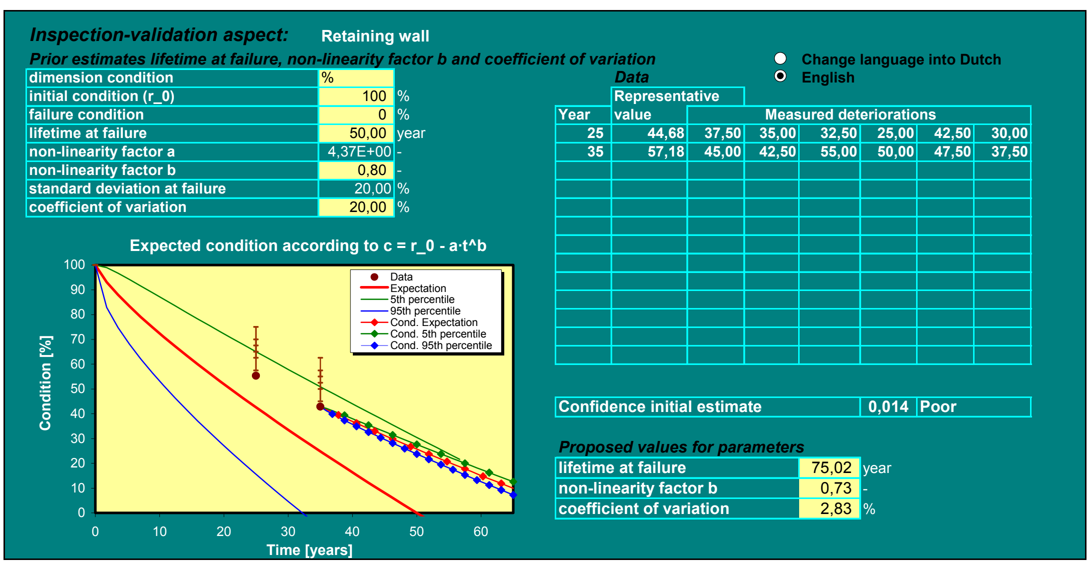

Figure 6. Inspection validation on representative values, reference steel thickness: 4 mm.

The temporal variability of the deterioration has been modelled as a so-called gamma process (van Noortwijk and Pandey, 2004). A gamma process is a non-decreasing stochastic process for which the increments are statistically independent, gamma-distributed random quantities with identical scale parameter. As far as the authors know, Abdel-Hameed (1975) was the first to propose the gamma process as a proper model for deterioration occurring random in time. He called this stochastic process the “gamma wear process”. An advantage of modelling deterioration processes through gamma processes is that the required mathematical calculations are relatively straightforward. The gamma process is suitable to model gradual damage monotonically accumulating over time, such as wear, fatigue, corrosion, crack growth, erosion, consumption, creep, swell, a degrading health index, et cetera.

The mathematical definition of the gamma process is given as follows. Recall that a random quantity X has a gamma distribution with shape parameter $v > 0$ and scale parameter $u > 0$ if its probability density function is given by:

$$\mathrm{Ga}(x \mid v, u) = \frac{u^v}{\Gamma(v)} x^{v-1} \exp\{-ux\}, \quad x > 0,$$

where

$$\Gamma(a) = \int_{t=0}^{\infty} t^{a-1} e^{-t} dt$$

is the gamma function for $a > 0$. It is assumed that the expected deterioration can be described as a power law between cumulative deterioration and time. Then, the gamma process with shape function ct^b, $t > 0$, and scale parameter $u > 0$ is a continuous-time stochastic process $\{X(t), t \geq 0\}$. Let $X(t)$ denote the cumulative amount of deterioration at time t, $t \geq 0$, and let the probability density function of $X(t)$, in accordance with the definition of the gamma process, be given by

$$f_{X(t)}(x) = \mathrm{Ga}(x \mid ct^b, u)$$

with expectation and variance

$$E(X(t)) = \frac{ct^b}{u}, \quad \mathrm{Var}(X(t)) = \frac{ct^b}{u^2}.$$

In order to apply the gamma-process model for the purpose of inspection validation, a statistical method for the parameter estimation of gamma processes is required. A typical data set consists of inspection times t_i, $i = 1,\ldots,n$, where $0 = t_1 < t_2 <\ldots< t_n$, and corresponding observations of the cumulative amounts of deterioration x_i, $i = 1,\ldots,n$, where $0 = x_1 \leq x_2 \leq\ldots\leq x_n$. The parameters of the gamma process have been estimated on the basis of inspection data by combining the methods of least squares and maximum likelihood. First, the power b has been estimated on the basis of a least-squares fit of the logarithm of the power-law model to the logarithm of the inspection data; that is, the least-squares estimate of b is

$$b = \frac{\sum_{i=1}^{n} \log\left(\frac{t_i}{t_n}\right) \log\left(\frac{x_i}{x_n}\right)}{\sum_{i=1}^{n} \left[\log\left(\frac{t_i}{t_n}\right)\right]^2}.$$

Second, the parameters c and u of the gamma process have been estimated by using the maximum-likelihood method. The maximum-likelihood estimators of c and u can be obtained by numerically maximizing the logarithm of the likelihood function of the independent deterioration increments when the value of the power b is given. This maximum-likelihood method was initially developed by Çinlar et al. (1977) and later rediscovered by van Noortwijk and Pandey (2004). Çinlar et al. (1977) successfully performed a statistical analysis of data on deterioration of concrete due to creep.

It should be noted that the proposed estimation method only works when there are at least three inspections available. This is due to the fact that three gamma-process parameters (i.e., c, b, and u) must be estimated. For situations in which there are less than three inspections, the statistical estimation method is revised in the sense that it partly uses the parameters of the a priori estimated deterioration process. In these situations, the coefficient of variation of the deterioration at the time at which the expected deterioration equals the failure level is assumed to be a priori known. In the event of a single inspection, the power b is assumed to be a priori known as well.

9 CONCLUSIONS

The inspection validation model can be used for a wide range of element types, in many different situations. All it requires is a consistent definition of condition and failure criteria. The IV model is a graphically orientated program, rather than a sophisticated mathematical black box. It merely supports the maintenance engineer in making maintenance advises.

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