Parameter Identification In Chloride Ingress From Accelerated Test Using Bayesian Network

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ABSTRACT: Chloride ingress into concrete is one of the main causes leading to the degradation of reinforced concrete (RC) structures. Important damages due to chloride-attack are reported after 10-20 years and thus, structures should be inspected periodically to ensure optimal levels of serviceability and safety. Modelling chloride ingress into concrete, therefore, becomes an important task to plan and quantify maintenance operations of structures. Relevant material and environmental parameters required for modelling could be determined from inspection data obtained after each inspection campaign. However, its assessment requires significant experimental time for collecting data that allow considering the time-dependency of the deterioration process. Data from accelerated test could be used as information about long-term performance of concrete or mortar under real exposure conditions if the scale factor reflecting the ratio between exposures times for normal and accelerated tests is determined. The main objective of this paper is to develop a method based on Bayesian updating to identify the 'real' (equivalent) exposure time from accelerated tests that is used to define the scale factor. The proposed methodology is first tested on simulated data and after implemented to real measurements.

1. INTRODUCTION

Chloride penetration into concrete is one of the main factors responsible for generating corrosion in reinforcing bar which in turn cause: reduction of reinforcement cross-section, loss of bond between steel and concrete, and concrete cracking and delamination (Bastidas-Arteaga and Schoefs 2012; Bastidas-Arteaga et al. 2011). These consequences lead to the reduction of serviceability and safety levels as well as the shortening of the service life of reinforced concrete (RC) structures. Most RC structures are designed for a lifetime of 50-100 years. However, under chloride attack, important damages are observed after 10-20 years (Kumar Mehta 2004; Poupard et al. 2006). Consequently, RC structures should be inspected periodically to ensure optimal levels of serviceability and safety during their structural life. Data collected after inspection campaigns is often used to determine parameters for chloride ingress or corrosion propagation models under specific environmental exposures. These parameters are very useful for lifetime assessment and optimisation of maintenance strategies (Bastidas-Arteaga and Schoefs 2012). However, under real exposure conditions, even for environments with larger chloride content (splash and tidal zones), the rate of chloride ingress into concrete is particularly slow. Consequently, a significant exposure time is required to collect inspection data useful to characterise the mid- and long-term durability behaviour of concrete and mortar. Non destructive chloride ingress measurements could be very useful to characterise the performance of cement-based materials subject to real conditions (Torres-Luque et al. 2014). However, many of these techniques are still under development.

This study is based on data obtained for two experimental conditions: natural and accelerated. Under natural exposure conditions, chloride ingress is a time-consuming process and thus, an accelerated procedure is introduced to speed up the penetration of chloride ions into concrete (section 3.1). Data from these tests could provide information about the mid- and long-term performance of concrete or mortar under real exposure conditions and it could be also used for testing new building or repair materials. The main challenge of this approach is to determine a scale factor reflecting the ratio between exposures times for normal and accelerated tests.

Bayesian network (BN) could be an effective tool for parameter identification. In inspection campaigns, the inspection depths are divided into intervals to determine the chloride content at given points in depth and times. The experimental data, therefore, was built in discretised form. The algorithm for treating both continuous and discrete variables is complex and requires significant computation effort, especially when chloride ingress is modelled as non-linear function (section 2.1). Consequently, a BN with discrete nodes was used to perform the updating. Some studies (Bastidas-Arteaga et al. 2012; Richard et al. 2012; Tran et al. 2014) proposed methodologies based on BN to identify model/material parameters by updating probabilities from real experiment data. In this study, BN is also used as a tool for parameter identification based on a chloride ingress model. Experiments consisting of normal and accelerated tests were carried out in the same concrete with the same environment conditions. Based on the approach proposed by Tran et al., (2014), data from normal test will be used to identify information about two model parameters: chloride surface concentration (C_s) and the chloride diffusion coefficient (D). This information will be after used as priori information in other BN to identify the equivalent exposure time from data obtained in the accelerated test. A scale factor representing the ratio between experimental time and equivalent time in accelerated test is then proposed.

2. PARAMETER IDENTIFICATION IN CHLORIDE INGRESS USING BN

2.1. Modelling chloride ingress

In this study, chloride ingress into concrete is modelled by (Luping and Gulikers 2007):

$$C(x,t) = C_s \operatorname{erfc}\left[\frac{x}{2\sqrt{\frac{D_0}{1-n}\left[\left(1+\frac{t'_{ex}}{t}\right)^{1-n}-\left(\frac{t'_{ex}}{t}\right)^{1-n}\right]\left(\frac{t'_0}{t}\right)^{n} t}}\right] \quad (1)$$

where $C(x,t)$ is the concentration of chloride ions at depth x and time t, C_s is the chloride concentration at the exposure surface, D_0 and t'_0 is a pair of known diffusion coefficient and age, t'_{ex} is the age of concrete at the start of exposure, n is the age factor, and erfc(.) is the complementary error function.

This equation is valid only under these assumptions: 1) concrete is a homogeneous material; 2) chloride binding is time-independent and linearly proportional to the free chloride concentration; 3) the effect of co-existing ions is constant; 4) the diffusion is one dimensional into semi-infinite space. This model is considered in this study to facilitate parametric studies to improve the BN configuration that minimise the identification error. In addition, it accounts, in a simplified way, for the time-dependency of the chloride ingress process.

2.2. Parameter identification using BN

Using BN for identifying parameters in chloride ingress has been investigated in some previous studies (Bastidas-Arteaga et al. 2012; Deby et al. 2008, 2012; Tran et al. 2014). In general, each parameter in the model is represented as a node in the BN. There is an arrow linking from a "parent node" to a "child node" to define the dependency between the two nodes. The Conditional Probability Table (CPT) in the BN describes the relationship between each pair of nodes. The CPT for each node could be built from numerical simulations or by real statistic data. The BN allows updating the statistical distributions of parameters in the network with new information from experimental results. In BN modelling of chloride ingress, parameters to identify are modelled as parent nodes and chloride content at different depth points and inspection times are modelled as child nodes. Inspection data (chloride concentrations at given points) is introduced in child nodes as evidences.

Tran et al. (2014) proposed a methodology to improve the BN configuration for parameter identification in chloride ingress models. They pointed out that there is a specific configuration of BN for each parameter that minimise the identification errors. For the surface chloride concentration (C_s), a BN with only one child node representing the chloride content at the surface at early inspection time provides a good identification. For the chloride diffusion coefficient (D), to minimise errors, the optimised BN configuration should consider child nodes representing the total inspection depth with optimal spatial discretisation intervals. Tran et al. (2014) also suggested that different boundaries should be used to define the ranges for child nodes to take advantage of information from deeper points where chloride content is low. These optimised configurations and numerical aspects are applied in this study to minimise the errors in parameter identification.

3. PARAMETER IDENTIFICATION WITH DATA FROM ACCELERATED TEST

3.1. Description of the experimental setup

The experimental setup of the natural and accelerated tests was carried out within the framework of the French MAREO project. It aimed at characterising the durability performance of new materials to repair RC components located in tidal zones by performing both normal and accelerated tests. For normal and accelerated tests, concrete slabs are placed in a tank with salted water. The exposure of the slabs ensures chloride ingress in one dimension. Tidal cycles (high and low) are simulated varying the level of water. For the accelerated tests, ventilators are used to dry the samples during the low tide cycle. The drying accelerates chloride ingress due to an increase of the capillarity sorption of concrete (Hong 1998). Normal tests are subjected to the same tidal cycles without drying. The test is automatically controlled via a Labview® program. The tanks are placed inside a building and its environmental conditions (room temperature, water salinity and relative humidity) are recorded.

For normal tests, the exposure time in laboratory, t_{exp}, could represent the exposure time in real conditions. However, for accelerated tests the chloride contents are larger, and consequently, the exposure time in lab t_{exp} must correspond to an equivalent time, t_{eq}, under natural exposure conditions ($t_{eq} > t_{exp}$).

3.2. Bayesian identification of t_{eq}

Chloride profiles obtained from normal tests could provide information about chloride content at depth x at real exposure times t_{exp}. However, those of accelerated test just can provide information about chloride content at depth x. Different BN configurations are then used for each tests. Figure 1 shows the BN used to model chloride ingress into concrete in normal tests where C_s and D_0 are two parent nodes and there are n child nodes $C(x_i,t_j)$ representing the discrete chloride concentration measurement in time and space i.e. at depth x_i and inspection time t_j. In accelerated tests, chloride ingress is modelled by the BN described in Figure 2 that has three parent nodes C_s, D_0 and t_{eq}. Child nodes in Figure 2 represent the chloride content at depth x_i.

The proposed approach for identifying t_{eq} is described in Figure 3. The first step of the methodology consists of using the BN and data from normal tests (Figure 1) to identify the two parameters C_s and D_0 respectively related to chloride exposure and concrete diffusivity. This step aims at characterising these two parameters under natural conditions. Then, posterior histograms of the parameters C_s and D_0 are then used in the second step as a priori information for the BN shown in Figure 2. The equivalent exposure time for accelerated test could be then identified by updating the BN with evidences obtained from accelerated test results.

If priori information about parameters C_s, D, and t_{eq} is not available, uniform distribution is often chosen (Bastidas-Arteaga et al. 2012; Hackl 2013; Robinson and Hartemink 2010). Normal and accelerated tests are performed on the same material subjected to the same environmental chloride concentration. Therefore, data from normal tests is used herein to provide priori information that reduces the level of uncertainty in the BN by improving the identification process of t_{eq}.

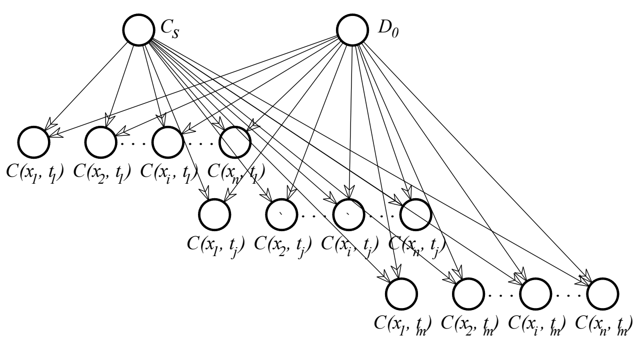

Figure 1: BN configuration for normal test

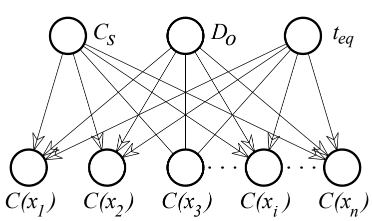

Figure 2: BN configuration for accelerated test

In fact, a fully BN consisting both natural and accelerated test could be applied here for the identification process. However, the 2-steps procedure (Figure 3) takes advantage of optimised configurations for identification of each parameter (C_s *or* D_0) that cannot be treated with a fully BN.

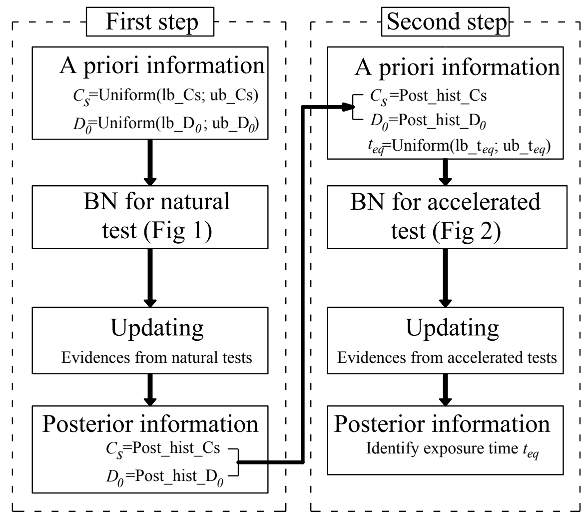

Figure 3: Flowchart of the proposed approach

4. APPLICATION TO NUMERICAL DATA

In practice it is difficult to obtain enough experimental data to validate the proposed procedure and to improve the configuration of the BN that minimises identification errors. Consequently, this section considers evidences created from simulated data (numerical evidences) to improve the configurations of BN corresponding to different inspection schemes. Section 4.1 details the generation of these simulated data. Each configuration is evaluated by the error of the identified parameter $Z_{identified}$ with respect to a theoretical value Z_{theory} as:

$$\mathrm{Error}(Z) = \frac{\left| Z_{identified} - Z_{theory} \right|}{Z_{theory}} 100\% \qquad (2)$$

where Z represents the mean or the standard deviation of the parameter to identify and the theoretical values Z_{theory} are used to generate chloride profiles from eq. (1).

4.1. BN modelling for natural tests

Most parameters in chloride ingress models are defined in continuous spaces. However, to avoid using approximate inference algorithms in BN

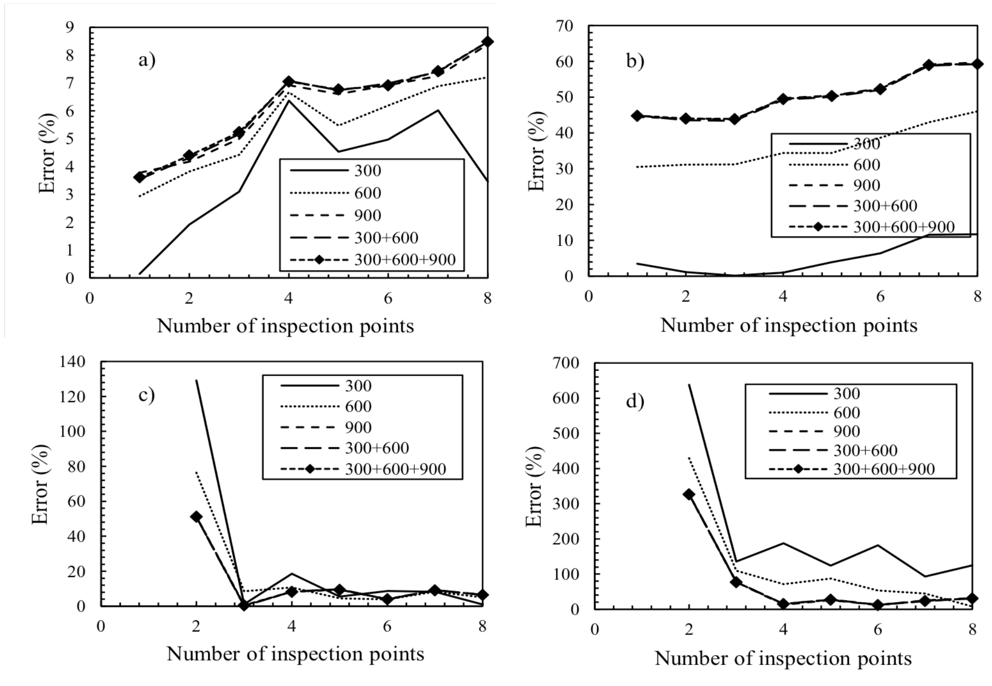

Figure 4: Identification errors: (a) Mean of C_s,(b) Standard deviation of C_s, (c) Mean of D_0, (d) Standard deviation of D_0

which will be a disadvantage when working with continuous variables, continuous variables should be replaced by discrete random variables (Straub 2009). Approximations due to the discretisation could also introduce error. Therefore, the choice of BN configuration is important to minimise error. The priori information and the discretisation of the parameters are described in Table 1. It is assumed that $t'_{ex} = t'_0 = 30$ days and $n = 0.5$.

Table 1: A priori information and discretisation of parameters in BN modelling for normal test

Parameter	*A priori information*	*Intervals per node*
C_s *[kg/m³]*	*Uniform (10^{-3} – 12)*	*60*
D_0 *[10^{-12}m/s²]*	*Uniform (0.4 – 3.5)*	*60*
C(x,t) [kg/m³]	-	*30*

Numerical evidences are generated from eq. (1) by using Monte Carlo simulations with the parameters given in Table 2. Data from different inspection schemes are combined to update the BN (Table 3). These schemes consider various inspection times with the same number of chloride profiles per scheme. The maximum number of days (900 days) corresponds to the time of exposure of normal tests.

Table 2: Theoretical values of parameters to identify

Parameter	*Distribution*	*Mean*	*COV*
C_s	*Lognormal*	*2.95 (kg/m³)*	*20%*
D_0	*Lognormal*	*10^{-12} (m/s²)*	*15%*

Table 3: Inspection schemes

Inspection scheme	*Number of chloride profiles*
300 days	*9000*
600 days	*9000*
900 days	*9000*
300+600 days	*4500 + 4500*
300+600+900 days	*3000+3000+3000*

With inspection time smaller than 900 days, chloride content at depth x > 20mm is almost null. Consequently, the total inspection depth is fixed at 20mm. Various BN configurations corresponding to different number of inspection points dividing the inspection depth into equal interval lengths are analysed to evaluate the identification errors. The interval lengths are larger than 3mm due to the accuracy of the semidestructive tests for determining chloride profiles.

The identification errors for C_s presented in Figure 4a and Figure 4b show that evidences obtained near the surface ($x \approx 0$) with early inspection time (t_{ins} = 300 days) could minimise the errors in the estimation of mean and standard deviation of C_s. Using more inspection points in depth could not improve the identification for this parameter. These behaviours are previously analysed and explained by (Tran et al. 2014). However, for D_0, combining evidences from different inspection times could improve the identification. This trend can be observed clearly in Figure 4d where the identification errors decrease when the evidences come from three inspection times (300+600+900) days. This is because the deterioration model herein takes into consideration the time-dependency of the chloride diffusion coefficient. This finding could very useful to plan inspection campaigns. Figure 4c and Figure 4d also reveal that using more inspection points could reduce the gap between identified and theoretical values for D_0.

4.2. BN modelling of accelerated test

Both normal and accelerated tests are carried out in the same concrete exposed to the same salted water and environmental conditions. Consequently, chloride concentration at surface (C_s) and chloride diffusion coefficient (D_0) in normal and accelerated tests could be considered approximately to be the same. To avoid any assumption about distribution shapes, posterior histograms of C_s and D_0 obtained after updating the BN of normal tests are then used directly as priori distribution in BN modelling of accelerated tests (Figure 3). To minimise the identification errors in normal tests, the histogram of C_s and D were obtained from improved BN configurations as previously discussed in section 4.1. According to Figure 2, the equivalent exposure time (t_{eq}) is the variable to identify. It is then modelled as a parent node with the priori distribution shown in Table 4.

Numerical evidences in the BN for accelerated tests are generated from the theoretical values presented in Table 4 at different inspection times varying from 300 to 3000 days. 9000 chloride profiles are generated for each inspection time. These inspection times reflect the equivalent times (t_{eq}) which are unknown in real practice to be identified. The total inspection depth is 30mm with 3mm of interval length, being sufficient to describe the penetration of chloride at 3000 days of exposure.

Table 4: A priori information and discretisation of parameters in BN modelling for normal test

Parameter	*Priori information*	*Intervals*
C_s [kg/m^3]	*Histogram from normal test* (10^{-3} - 12)	60
D_0 [m/s^2]	*Histogram from normal test* (4.10^{-13} - $3.5.10^{-12}$)	60
t_{eq} [days]	*Uniform* (0-3600)	100
$C(x)$ [kg/m^3]	-	30

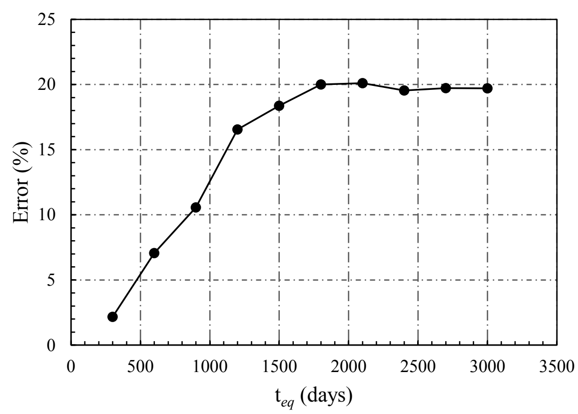

Figure 5: Identification error for the mean t_{eq}

The error on the identification of the equivalent exposure times from accelerated tests is shown in Figure 5. The error for all cases is smaller than 20%. Especially, errors at 300, 600, and 900 days are smaller than other cases. It is because priori information of C_s and D_0 was obtained from normal tests at these exposure times and then it reduces the identification errors. When dealing with real data, the identified values of equivalent exposure times could be used to calculate scale factors.

5. APPLICATION TO REAL DATA

5.1. Experimental data

Destructive tests were carried out to determine chloride profiles from both normal and accelerated tests at different exposure times (Table 5). Each chloride profile has 42mm in depth with a discretisation depth of 3mm. This gives a total of 14 inspection points per profile.

Table 5: Exposure times and number of chloride profiles

	Normal			Accelerated		
	T1	T2	T3	T1	T2	T3
t_{exp} (days)	65	207	320	65	212	436
Number of profiles	3	3	3	6	6	6

5.2. Identification of the scale factor k

A scale factor in accelerated tests can be defined as a ratio between the exposure time in the experiment (t_{exp}) and the equivalent exposure time (t_{eq}):

$$k = t_{eq} / t_{exp} \tag{3}$$

The experimental exposure times in accelerated tests (t_{exp}) are given in Table 5. The equivalent exposure times (t_{eq}) are determined by the procedure given in Figure 3. Improved BN configurations defined according to the findings described in section 4.1 are used to take advantage of limited data and minimise the identification errors in normal tests. Thus, evidences at the surface ($x \approx 0$) from chloride profiles obtained at inspection time T1 are used for BN updating to obtain posteriori histogram of C_s. Data combining three inspection times (T1 + T2 + T3) with 14 inspection points in depth are used to obtain posterior histogram of D_0. These posterior histograms are then used as priori information in BN modelling of accelerated test. Equivalent exposure times are determined by updating the BN with evidences from accelerated tests and scale factors are then computed from Eq. (3).

The results for equivalent exposure times and scale factors are given in Table 6. Identified values of t_{eq} show an expected trend that a longer exposure time (t_{exp}) in the laboratory will be equivalent to a larger value of t_{eq}. By plotting the scale factors with the experimental times with a spline (Figure 6), it is noted that the scale factor is not constant. At early inspection time, this factor is high and then it decrease with time. This trend is explained by the time-dependency of the chloride diffusion coefficient (Tang and Nilsson 1996). The values of scale factors could be more accurate if more experimental data is available.

Table 6: Real exposure and equivalent times

Accelerated test	T1	T2	T3
t_{exp} [days]	65	212	436
t_{eq} [days]	725.2	935.9	1050.3

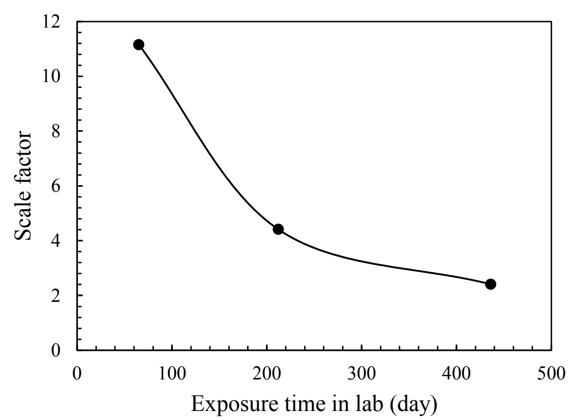

Figure 6: Scale factor for accelerated tests

6. CONCLUSIONS

Chlorides ions are critical agents leading to reinforcement corrosion of RC structures. The characterisation of the performance of cement-based materials under real conditions requires significant experimental times. Consequently, this study proposed a methodology for characterising these materials by using accelerated tests and BN updating. The proposed approach allows determining a scale factor for the accelerated test. Therefore, information about mid- and long-term performance of concrete or mortar under real exposure condition could be obtained from accelerated experiments in lab. This information is useful to characterise the performance of new repair techniques or cement-based repair materials.

This paper presented the first findings on this area. Future works will focus on:

- obtaining more experimental data to improve the identification,
- identification of the age factor in the chloride ingress model eq. (1), and
- consideration of measurement and model errors.

7. ACKNOWLEDGEMENTS

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