Bayesian identification of uncertainties in chloride ingress modeling into reinforced concrete structures

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ABSTRACT: Chloride penetration is one of the major causes leading to the degradation of reinforced concrete structures by reinforcement corrosion. Therefore, its modeling is a major component in planning and quantifying maintenance operations of the structure. Modeling needs relevant material and environmental parameters determined from experimental measurements. The main objective of this paper is to develop a method for identifying the model parameters of chloride penetration into concrete from measurements using an inverse analysis model based on probabilistic principles. The results of the identification indicate that the Bayesian approach may be useful to identify the model parameters from real data.

1 INTRODUCTION

Corrosion is the major cause of degradation of reinforced concrete (RC) structures. RC structures corrode when they are subjected to the exposure to chlorides or carbon dioxide in the environment (Duprat, 2007). This study focuses on the penetration of chlorides into concrete. Chloride ingress induces corrosion when a threshold concentration of chlorides reaches the reinforcement.

Modeling chloride penetration into concrete is crucial for optimizing maintenance interventions (inspection and repair) of these structures (Duracrete, 2000). Chloride penetration is a very complex process influenced by many factors –i.e., concrete properties, environment, etc. (Bastidas-Arteaga et al., 2011). Consequently, its modeling should be based on experimental measurements in order to make relevant lifecycle predictions and maintenance recommendations. One type of experimental test could be used to determine the profiles of chloride content at a point of the structure. However, maintenance decision-making cannot be only based on these measurements because these results are highly variable and measurement error is very significant (Bonnet et al., 2009). Therefore, a large number of measurements could be needed to determine the relevant input parameters for modeling. Taking into account that these tests are expensive and difficult to implement in practice, the use of experimental results should be optimized. This optimization could be therefore based on a probabilistic approach that accounts for uncertainties.

Within this context, this paper proposes a probabilistic approach based on Bayesian inference to optimize the identification of the input parameters for two chloride penetration models. The proposed approach will consider the randomness related to both material properties and mechanisms of chloride ingress. The Bayesian network (BN) methodology is a powerful approach for such updating challenges, especially when the available information evolves in time and the updating must be done in real time (Straub and der Kiureghian, 2010). That is the case for the bridge application in this paper (Section 4).

Section 2 describes the analytical models of chloride penetration and Bayesian formulation used to identify the input random variables of the problem. To validate the Bayesian method we used numerical samples obtained from Monte Carlo simulations (Section 3). Finally, Section 4 will present an application of the proposed approach for the identification of model parameters of chloride penetration in a real structure.

2 APPLICATION OF BAYES THEOREM TO CHLORIDE DIFFUSION MODELS

Assessment of corrosion effects on RC structures is a difficult task because several deterioration mechanisms interact in the process. Chloride-induced corrosion involves the interaction between three mechanisms: chloride ingress, corrosion of reinforcing steel and concrete cracking. Chloride ingress induces corrosion initiation of the reinforcing bars. The accumulation of corrosion products in the steel/concrete interface generates concrete cracking, which plays an important role in the steel corrosion rate when excessive concrete cracking is reached. Based on the previous considerations, the corrosion process is divided into two stages namely 'corrosion initiation' and 'corrosion propagation'. The following sections describe firstly the physical phenomena as well as present the adopted analytical models to determine the time to corrosion initiation caused by chloride ingress. Afterwards, it presents the Bayesian formulation to identify the input random variables from real measurements.

2.1 *Simplified model for chloride diffusion*

The second law of diffusion of Fick is generally used to model chloride flow into concrete (Tuutti, 1982). Assuming that concrete is homogeneous, isotropic, saturated and subjected to a constant concentration of chlorides at the surface C_s, the solution of differential equations is expressed as the concentration of chloride ions $C(x, t)$ at depth x and time t, as follows:

$$C(x,t) = C_s\left[1 - erf\left(\frac{x}{2\sqrt{Dt}}\right)\right] \tag{1}$$

where D is the effective chloride diffusion coefficient and erf $(\cdot)$ is the error function. The Bayes theorem can be used to calculate the probability distributions of the random variables in this problem (Naïm et al., 2007). In this case, the main purpose of the Bayesian identification is to identify the randomness of D and C_s. Assuming that D and C_s are two independent random variables (eq. (3)), the probability of assessment of a chloride concentration at a point x and a given time t, $p(C(x, t))$, writes (Nguyen, 2007):

$$p\left(C(x,t)\right) = \sum_{D,C_s} p\left(C(x,t)\middle|D,C_s\right)p\left(D,C_s\right) \tag{2}$$

with

$$p\left(D,C_s\right) = p\left(D\right)p\left(C_s\right) \tag{3}$$

In eq. (2), the conditional probability $p(C(x, t)|\ D, C_s)$ must already be known. This conditional probability relates the chloride content $C(x, t)$ to the material characteristics. In other words, it accounts for transfer mechanisms, such as the modeled by eq. (1), in a purely probabilistic form. This probability could be computed based on the conditional probability table (CPT) of the BN. The CPT can be determined from:

1. a given model –e.g., eq. (1) or
2. expert knowledge.

Once $p(C(x, t))$ is computed, *a posteriori* probability distributions (distributions to be identified) can be calculated from a set of measurements of $C(x, t)$. $p(C(x, t)|o)$ represents the probability distribution of $C(x, t)$ given evidence o. In this case, chloride profiles are used as evidence, assuming that measurements are perfects. Thus, for identifying the probability distribution of the effective chloride diffusion coefficient, the application of the Bayes theorem gives:

$$p\left(D\middle|o\right) = p\left(D\middle|C(x,t)\right)p\left(C(x,t)\middle|o\right) \tag{4}$$

with

$$p\left(D\middle|C(x,t)\right) = \frac{p\left(C(x,t)\middle|D\right)p\left(D\right)}{p\left(C(x,t)\right)} \tag{5}$$

Similarly for the identification of the distribution of the concentration of chlorides at the surface C_s:

$$p\left(C_s\middle|o\right) = p\left(C_s\middle|C(x,t)\right)p\left(C(x,t)\middle|o\right) \tag{6}$$

with

$$p\left(C_s\middle|C(x,t)\right) = \frac{p\left(C(x,t)\middle|C_s\right)p\left(C_s\right)}{p\left(C(x,t)\right)} \tag{7}$$

The determination of conditional probabilities is carried out herein by Bayesian learning and inference using the Netica® software. Note that the error of the model can be also updated by a BN as suggested by (Deby et al., 2011).

2.2 *Duracrete model*

The closed-form solution of Fick's diffusion law can be easily used to predict the time to corrosion initiation. However, eq. (1) is valid only when RC structures are saturated and subjected to constant concentration of chlorides on the exposed surfaces. These conditions are rarely present for real structures because concrete is a heterogeneous material that is frequently exposed to time-variant surface chloride concentrations. Besides, this solution does not consider chloride binding capacity, concrete aging and other environmental factors as temperature and humidity (Saetta et al, 1993; Bastidas-Arteaga et al, 2010, 2011).

The European Union project (Duracrete, 2000) proposes an expression similar to eq. (1) which considers the influence of material properties, environment, concrete aging and concrete curing on the chloride diffusion coefficient:

$$C(x,t) = C_{s,D}\left[1 - erf\left(\frac{x}{2\sqrt{k_e k_t k_c D_o \left(t_o/t\right)^{n_D} t}}\right)\right] \tag{8}$$

where $C_{s,D}$ is the chloride surface content computed for this model, k_e is a factor taking into account the characteristics of the environment (k_e = 0.924 for a tidal zone and k_e = 0.676 for an atmospheric zone), k_t is a factor defined according to the method used to determine the diffusion coefficient D_o, k_c is a factor which takes into account the curing time (k_c = 0.8 for 28 days), t_o is the time for which D_o has been measured and n_D is the aging factor.

Table 1 presents some values of n_D for different types of concrete in the atmospheric environment according to (Duracrete, 2000). In all cases, n_D follows a beta distribution. These distributions are plotted in Figure 1.

Table 1. Values of n_D for different types of ciment

Cement type	Mean	Std. dev.	a	b
Ordinary Portland (OPC)	0.65	0.07	0	1
Portland with Fly Ash (PFA)	0.66	0.07	0	1
Blastfurnace slag (GGBS)	0.85	0.07	0	1
Portland with Silica Fume (SF)	0.79	0.07	0	1

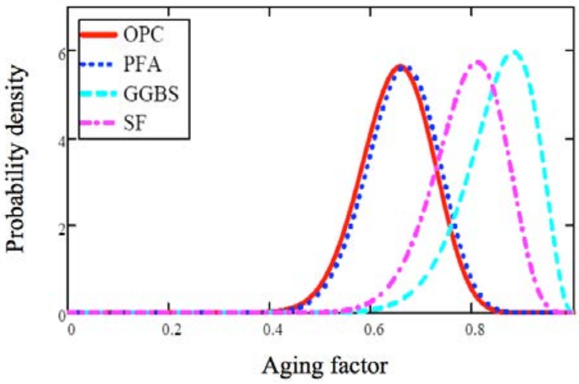


Figure 1. Distributions of n_D.

Some parameters of eq. (8) could be considered as constant taking into account the characteristics of the structure. For instance, it is possible to suppose that the following factors are constant: the exposure zone, the method to estimate D_o and the curing time. Then, k_e, k_t and k_c are constant and there are three random variables to identify: D_o, $C_{s,D}$ and n_D. Assuming that D_o, $C_{s,D}$ and n_D are independent random variables, $p(C(x,t))$ becomes:

$$p(C(x,t)) = \sum_{D_o,C_{s,D},n_D} p\left(C(x,t)\middle|D_o,C_{s,D},n_D\right)p\left(D_o,C_{s,D},n_D\right) \quad (9)$$

with

$$p\left(D_o,C_{s,D},n_D\right) = p\left(D_o\right)p\left(C_{s,D}\right)p\left(n_D\right) \quad (10)$$

Note that D_o and $C_{s,D}$ are modeled as independent random variables due to physical considerations. D_o is directly related to material properties whereas $C_{s,D}$ depends on the environmental exposure. However, the assumption of independence for D_o and n_D is more questionable because both parameters are related to material properties. This point is not treated in the paper but recent methods allow to extent BN to correlated random variables (Bensi et al., 2011). The conditional probability $p(C(x,t)|D_0,C_{s,D},n_D)$ in eq. (9) must already be known. It is also computed based on the CPT of the BN. When $p(C(x,t))$ is determined, *a posteriori* distributions for D_o, $C_{s,D}$ and n_D can be calculated from a set of measurements of chloride profiles. Thus, the application of the Bayes theorem to identify the probability distribution of D_o gives:

$$p\left(D_o\middle|o\right) = p\left(D_o\middle|C(x,t)\right)p\left(C(x,t)\middle|o\right) \quad (11)$$

with

$$p\left(D_o\middle|C(x,t)\right) = \frac{p\left(C(x,t)\middle|D_o\right)p\left(D_o\right)}{p\left(C(x,t)\right)} \quad (12)$$

For the identification of the distribution of $C_{s,D}$:

$$p\left(C_{s,D}\middle|o\right) = p\left(C_{s,D}\middle|C(x,t)\right)p\left(C(x,t)\middle|o\right) \quad (13)$$

with

$$p\left(C_{s,D}\middle|C(x,t)\right) = \frac{p\left(C(x,t)\middle|C_{s,D}\right)p\left(C_{s,D}\right)}{p\left(C(x,t)\right)} \quad (14)$$

Finally, for the identification of the distribution of n_D:

$$p\left(n_D\middle|o\right) = p\left(n_D\middle|C(x,t)\right)p\left(C(x,t)\middle|o\right) \quad (15)$$

with

$$p\left(n_D\middle|C(x,t)\right) = \frac{p\left(C(x,t)\middle|n_D\right)p\left(n_D\right)}{p\left(C(x,t)\right)} \quad (16)$$

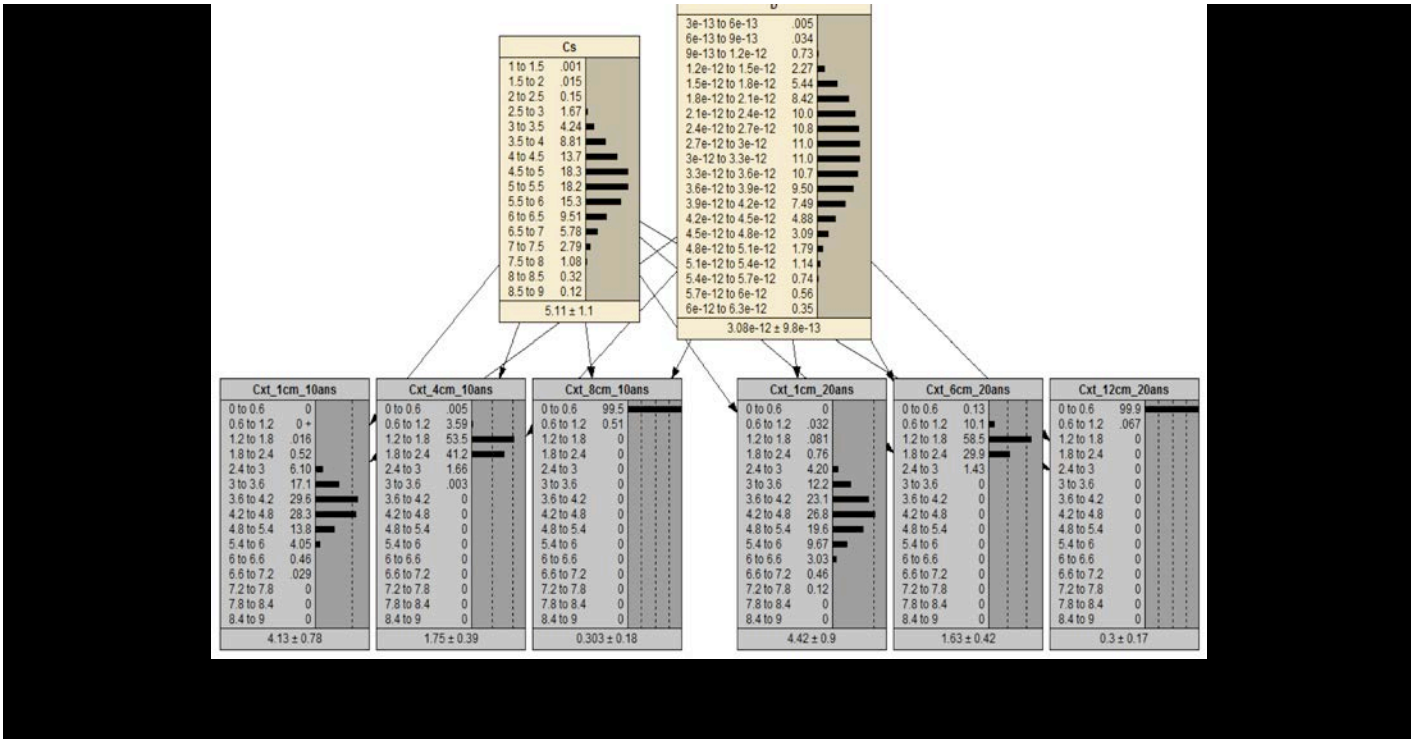
The determination of conditional probabilities is also carried out by using the Netica® software.

3 IDENTIFICATION USING NUMERICAL SAMPLES

Bayesian updating provides *a posteriori* information that considers real observations (evidence) of the studied phenomenon. This evidence could be obtained both from experimental measurements or expert knowledge. Before identifying random variables from real evidence, this section tests the performance of the BN and optimizes its configuration. Towards this aim, we use numerical evidence obtained from known input random variables. Therefore, we will focus on the Bayesian identification of the distributions of D and C_s for the diffusion model presented in eq. (1).

3.1 *Generation of numerical evidence*

For the sake of simplicity, the generation of numerical evidence assumes that D and C_s follow normal distributions with the parameters presented in Table 2. However, these random variables usually follow lognormal distributions (Duracrete, 2000; Vu and Stewart, 2000). These distributions were used to generate 3000 random values for D and C_s from Monte Carlo simulations. Then, each set of values was used to compute numerical chloride profiles at



different depths and times. These results serve afterwards to compute the probability that $C(x,t)$ belongs to a given interval for different depths. For instance, Table 3 presents the numerical evidence estimated from simulations for t = 10 years. These results are given in terms of probability of belonging to each interval. As expected, the probabilities of containing higher chloride concentrations (i.e., $C(x,t) > 2$ kg/m^3) increase for small depths because the exposure time is short.

Table 2. Mean and std. dev. for C_s and D

μ_{Cs} (kg/m^3)	σ_{Cs} (kg/m^3)	μ_D (m^2/s)	σ_D (m^2/s)
5	1	3×10^{-12}	3×10^{-13}

Table 3. Numerical evidence at 10 yr.

Interval (kg/m^3)	x = 1cm	x = 4cm	x = 8cm
0.0 - 0.6	0	0.00033	0.992333
0.6 - 1.2	0.0003	0.05467	0.007667
1.2 - 1.8	0.0017	0.46333	0
1.8 - 2.4	0.0147	0.42667	0
2.4 - 3.0	0.0757	0.05433	0
3.0 - 3.6	0.1810	0.00067	0
3.6 - 4.2	0.2666	0	0
4.2 - 4.8	0.2620	0	0
4.8 - 5.4	0.1380	0	0
5.4 - 6.0	0.0500	0	0
6.0 - 6.6	0.0090	0	0
6.6 - 7.2	0.0010	0	0
7.2 - 7.8	0	0	0
7.8 - 8.4	0	0	0
8.4 - 9.0	0	0	0
Total	1	1	1

3.2 *Identification of model parameters*

This section presents the approach taken into account for identifying both the mean and standard deviation of D and C_s from numerical evidence. Figure 2 shows the adopted network configuration. The characteristics of the network (number of nodes, position and time to determine $C(x,t)$) were defined after testing several configurations (Nguyen, 2011). There are:

- two parent nodes representing the random variables to identify (C_s and D) and
- six child nodes representing chloride concentrations $C(x,t)$ at different times (10 and 20 years) and depths (1, 4 and 8cm.).

Bayesian networks algorithms only account for discrete random variables. Therefore the random variables D and C_s must be discretized. The chloride surface concentration was discretized into 16 intervals varying between 1 and 9 kg/m^3. The chloride diffusion coefficient was divided into 20 intervals ranging from 3×10^{-13} to 6.3×10^{-12} m^2/s (Figure 2). The conditional probability tables are obtained from simulations using eq. (1) and the software Netica®.

At the beginning of the identification, it is assumed that both C_s and D follow uniform distributions (*a priori* distributions). This assumption increases the computational time (number of iterations until convergence) but avoids making any assumption about the distribution shape. This problem is especially important on distribution tails where there is few information but high influence on reliability. *A posteriori* distributions of C_s and D are computed when numerical evidence is introduced in the network. To improve the identification, we use an iterative procedure where *a posteriori* distributions of the iteration i will be used as *a priori* distributions for the iteration i + 1. All iterations are always performed with the same numerical evidence.

Figures 2 and 3 show the evolution of both the mean and standard deviation C_s and D after 3 iterations. For the first iteration, the identified mean and standard deviation of C_s and D are very different from theoretical values used in the generation of the numerical evidence (Table 2). The difference is more appreciable in the identification of the standard deviation. However, for both random variables, the mean and standard deviation are close to the theoretical values when the number of iterations increases.

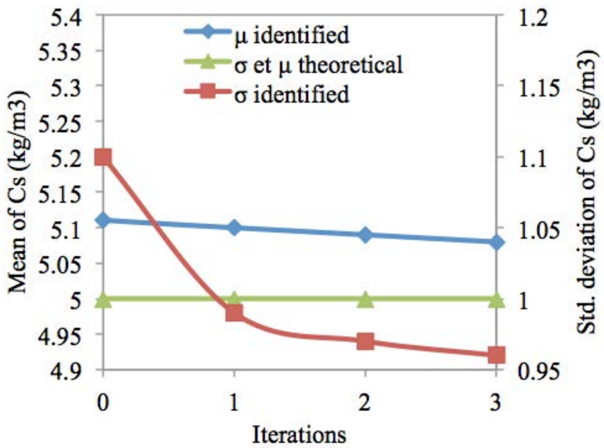


Figure 3. Evolution of the mean and the standard deviation of C_s with the iterations.

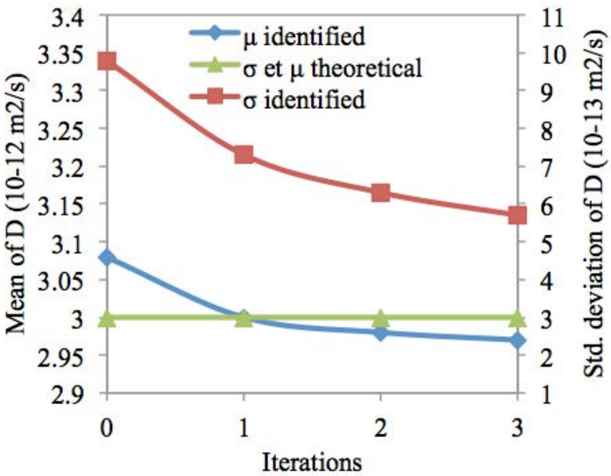


Figure 4. Evolution of the mean and the standard deviation of D with the iterations.

Figure 5 compares the numerical profiles of chloride content at t = 10 years (points) with the mean profile and its 5% and 95% quantiles identified after three iterations. It is observed that most of the numerical profiles are in the area corresponding to 90% probability. Therefore, it is possible to conclude that the network configuration used for identification Bayesian might be useful to identify the randomness of model parameters from real data.

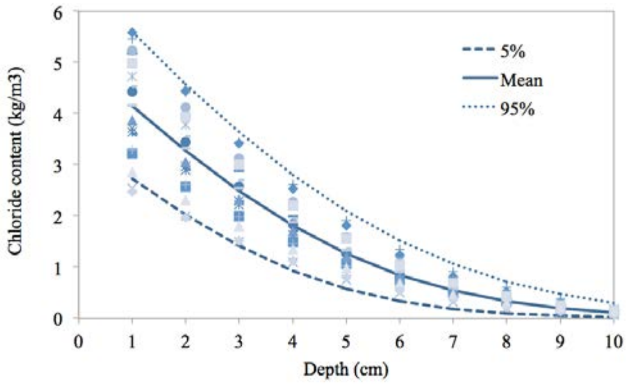


Figure 5. Comparison between simulated profiles (points) and the mean and quantiles.

4 IDENTIFICATION OF DIFFUSION PARAMETERS FROM MEASUREMENTS

4.1 *Problem description*

This section presents the application of Bayesian inference to the identification of random variables based on measurements on the Ferrycarrig Bridge (Figure 6). This structure is located in Wexford on the southeast coast of Ireland and passes over the River Slaney. Built in 1980, the structure is located in a marine environment. In 2007, the manager Eirspan completed an inspection of the main structure. Chloride content profiles were collected from different beams of the bridge during the inspection. These beams were exposed to an atmospheric marine environment. The identification performed in this section will consider these experimental results as well as the Duracrete model (eq. (8)). This model is more appropriate than the simplified solution of Fick law because it considers the influence of other parameters as discussed in section 2.2.


Figure 6. Ferrycarrig Bridge.

4.2 *Bayesian identification*

The random variables to identify are defined taking into account the characteristics of the bridge.

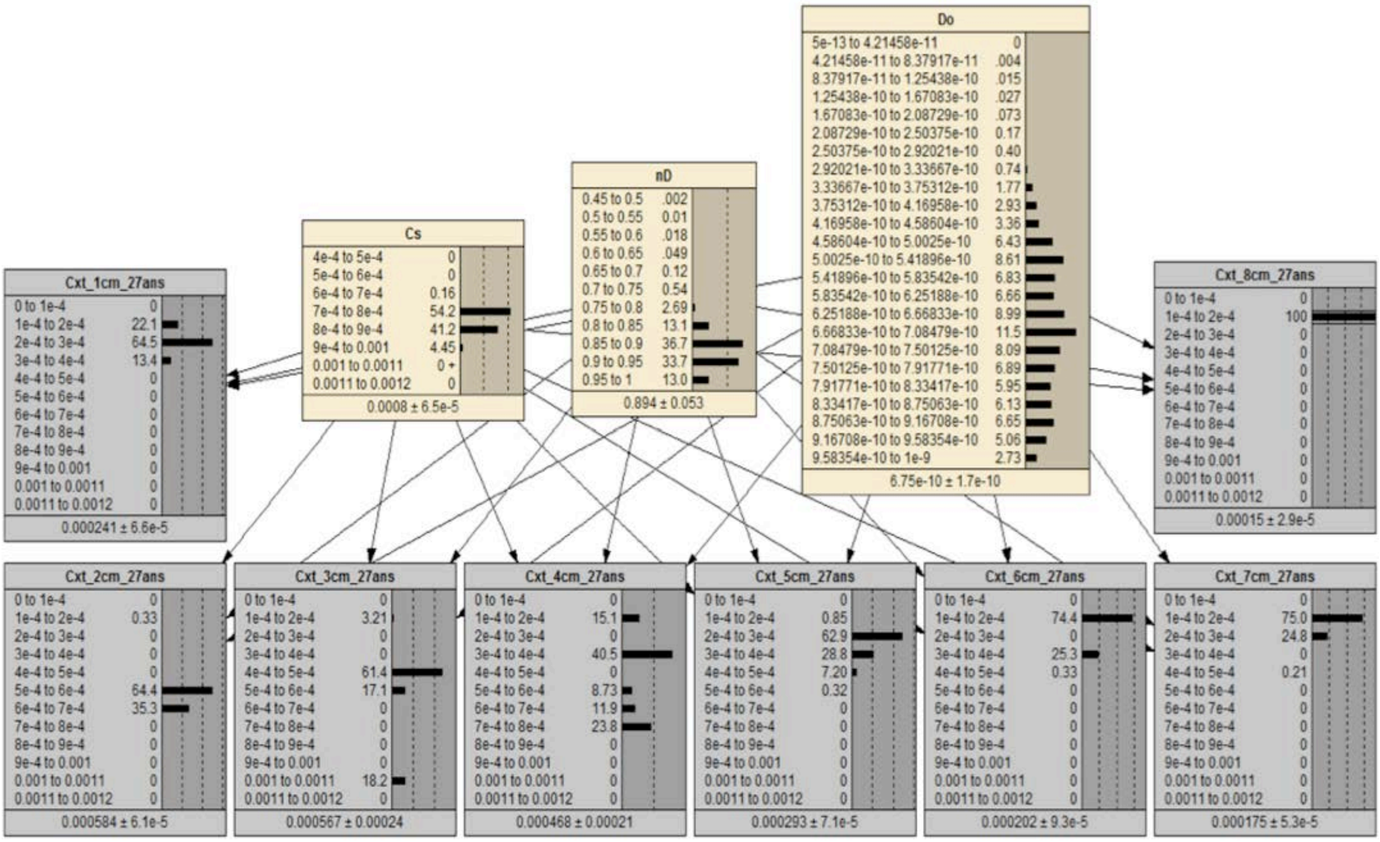


Figure 7. Bayesian network to identify the diffusion parameters of the Duracrete model

Therefore, some parameters of eq. (8) are considered as constant. For instance, it is possible to assume that $k_e = 0.676$ because the beams are placed in an atmospheric zone. If we consider that the identified chloride diffusion coefficient corresponds to a migration test the factor $k_t = 1$. Assuming that the curing time is $t_o = 28$ days, the factor $k_c = 0.8$. And the exposure time was 27 years when inspection was carried out. Taking into account these simplifications, the problem is reduced to identify three random variables: $C_{s,D}$, D_o and n_D.

Figure 7 depicts the configuration of the Bayesian network used in identification. This network has the following characteristics:

– three parent nodes representing the random variables to identify ($C_{s,D}$, D_o and n_D) and
– eight child nodes representing chloride concentrations $C(x,t)$ at different depths (1 to 8 cm.) and after 27 years of exposure.

As previously mentioned, the identification is based on experimental results. Table 4 presents the experimental evidence computed from measurements of total chloride concentrations on several points of the Ferrycarrig Bridge. As expected, the probability of belonging to a state with low chloride content increases for larger depths.

The following discretization was considered for the random variables to identify (Figure 7):

– 11 intervals for n_D within the interval [0.45, 1]. These limits were defined according to the distributions presented in Figure 1.
– 8 intervals for $C_{s,D}$ within the interval [4×10^{-2}, 12×10^{-2}] % per weight of concrete. These values were adopted taking into account the experimental results presented in Table 4.
– 24 intervals for D_o within the interval [5×10^{-13}, 1×10^{-9}] m^2/s. This interval was defined according to values found in the literature for different concretes (Duracrete, 2000; Vu and Stewart, 2007; Duprat, 2007).

Table 4. Experimental evidence.

$C(x,t)$ (10^{-2} % per	Depth (cm)							
wt. of concrete)	1	2	3	4	5	6	7	8
0 - 1	0	0	0	0	0	0	0	0
1 - 2	0.2	0.2	0.2	0.2	0.2	0.6	0.6	1
2 - 3	0.6	0	0	0	0.2	0	0.2	0
3 - 4	0.2	0	0	0.2	0.2	0.2	0	0
4 - 5	0	0	0.4	0	0.2	0.2	0.2	0
5 - 6	0	0.4	0.2	0.2	0.2	0	0	0
6 - 7	0	0.4	0	0.2	0	0	0	0
7 - 8	0	0	0	0.2	0	0	0	0
8 - 9	0	0	0	0	0	0	0	0
9 -10	0	0	0	0	0	0	0	0
10 - 11	0	0	0.2	0	0	0	0	0
11 -12	0	0	0	0	0	0	0	0
Total	1	1	1	1	1	1	1	1

Considering that there is no information about the distribution shape of $C_{s,D}$, D_o and n_D, it is assumed that these random variables follow uniform *a priori* distributions for the first iteration. Following the same iterative procedure described in section 3.2, we carried out five iterations to illustrate the identification process. Table 5 shows the *a posteriori* mean and standard deviation of $C_{s,D}$, D_o and n_D. It is observed that after five iterations, the mean and standard deviation gradually lead to constant values. These results are fairly stable after five iterations. However, the results will be more accurate if the number of iterations increases.

Table 5. *A posteriori* results for $C_{s,D}$, D_o and n_D.

Variable	Iteration	Mean	Std. dev
$C_{s,D}$ (% per wt. of concrete)	0	0.0809	0.01
	1	0.0803	0.0078
	2	0.0799	0.0069
	3	0.08	0.0065
	4	0.0801	0.0064
	5	0.0802	0.0064
D_o ($\times 10^{-10}$ m^2/s)	0	4.91	2.8
	1	5.66	2.5
	2	6.38	2
	3	6.75	1.7
	4	6.81	1.5
	5	6.75	1.3
n_D	0	0.804	0.14
	1	0.844	0.11
	2	0.879	0.075
	3	0.894	0.053
	4	0.898	0.044
	5	0.9	0.038

Afterwards, this work focuses on determining which type of distribution is most appropriate to represent the random variables of $C_{s,D}$, D_o and n_D. To find the best kind of distribution, we compute the "log likelihood" value for some distribution types after 5 iterations. This estimation is performed using the distribution fitting tool in Matlab®. These results are presented in Table 6. The selection of the pdf type will rely both on the physical understanding of the variations of each random variable (range, shape, etc.) and this estimate.

For $C_{s,D}$, the log likelihood is larger for a lognormal distribution according to the results presented in Table 6. Consequently, this random variable will be represented by a lognormal distribution with a mean of 0.0802 % per wt. of concrete and a standard deviation of 0.0064 % per wt. of concrete. It is expected that $C_{s,D}$ follows a lognormal distribution because this variable cannot physically take negative values. This kind of distribution is also widely found in the literature –e.g., Duracrete (2000), Vu and Stewart (2000), Duprat (2007).

For D_o, the largest log likelihood value corresponds to a beta distribution. However, there is no significant difference with the log likelihood values obtained for the gamma and lognormal distributions. The beta distribution could not be appropriate to represent this random variable because it is defined into the range [0, 1]. Therefore, D_o could be represented by gamma or lognormal distributions with the following parameters: mean = 6.75×10^{-10} m^2/s, standard deviation =1.3×10^{-10} m^2/s, shape = 27.2 and scale = 2.48×10^{-11}. These types of distributions have been also reported for other authors in the literature. Kirkpatrick et al. (2002) found that this variable follows a gamma distribution. Wallbank (1989), Hoffman et al. (1994) and Enright and Frangopol (1998) conclude that this random variable follows a lognormal distribution. The identified mean value of D_o could seem higher with respect to different values reported in the literature. The difference is explained by the fact that this diffusion coefficient is computed from results of total chloride concentration.

Table 6. Log likelihood test for the identified random variables.

Variable	Distribution	Log likelihood
$C_{s,D}$ (/wt. of concrete)	Normal	834.63
	Lognormal	836.47
	Weibull	825.00
	Gamma	835.91
	Beta	835.91
D_o (m^2/s)	Normal	2092.18
	Lognormal	2093.37
	Weibull	2089.73
	Gamma	2093.43
	Beta	2093.44
n_D	Normal	195.47
	Lognormal	195.42
	Weibull	189.60
	Gamma	195.46
	Beta	190.70

For n_D, the maximum log likelihood value corresponds to a normal distribution. Nevertheless, this kind of distribution is not appropriate to represent this random variable because it could take values outside of the range [0, 1] that are not allowed by the Duracrete model. Thus, it is assumed that the aging factor follows a beta distribution that takes only values between 0 and 1. Duracrete (2000) also suggest this kind of distribution. The parameters for n_D are: mean = 0.9 and the shape parameters a = 56.39 and b = 6.18.

5 CONCLUSIONS

Chloride ions have been recognized as a critical agent leading to reinforcement corrosion of RC structures. Therefore, the prediction of chloride penetration into concrete is necessary for optimal management of RC structures placed in chloride-contaminated environments. Prediction results depend on both the quality of chloride ingress models and their input data. This work focused on the assessment of comprehensive input data from real measurements by Bayesian identification. The Bayesian approach can update information in the model by an iterative method. In other words, the Bayesian method can effectively take advantage of the limited number of experimental measurements. The results of the identification of numerical evidence generated by Monte Carlo simulations indicate that the identified values are close to the theoretical values. The approach was also used to identify random variables on a more complex model from measurements on a real structure.

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REFERENCES

Bastidas-Arteaga, E. Chateauneuf, A. Sánchez-Silva, M. Bressolette, Ph. Schoefs, F. 2010. Influence of weather and global warming in chloride ingress into concrete: a stochastic approach. *Structural Safety* 32:238-249.

Bastidas-Arteaga, E. Chateauneuf, A. Sanchez-Silva, M. Bressolette, P. & Schoefs, F. 2011. A comprehensive probabilistic model of chloride ingress in unsaturated concrete. *Engineering Structures* 33:720-30.

Bensi, M. der Kiureghian, A. Straub, D. 2011. Bayesian network modeling of correlated random variables drawn from a Gaussian random field. *Structural Safety* 33:317-332.

Bonnet, S. Schoefs, F. Ricardo, J. & Salta, M. 2009. Effect of error measurements of chloride profiles on reliability assessment. In: 1*0th International Conference on Structural Safety and Reliability*, Japon.

Deby, F. Carcasses, M. Sellier, A. 2009. Toward a probabilistic design of reinforced concrete durability: application to a marine environment. *Materials and Structures.* 42:1379-1391.

Duprat, F. 2007. Reliability of RC beams under chloride-ingress. *Construction and building materials* 21:1605-16.

Duracrete. 2000. *Statistical quantification of the variables in the limit state functions*. The European union, BriteEuRam III, contract BRPR-CT95-0132, Project BE95-1347. Report No. BE95-1347/R7.

Enright, M.P. Frangopol D.M. 1998. Probabilistic analysis of resistance degradation of reinforced concrete bridge beams under corrosion. *Eng Struct* 20(11):960–71.

Hoffman, P.C. Weyers, R.E. 1994. Predicting critical chloride levels in concrete bridge decks. In: Shueller GI, Shinozuka M, Yao JTP, editors. *Sructural safety & reliability, ICOSSAR'93 proceedings*. Innsbruck: Balkema. p. 957–9.

Kirkpatrick, T.J. Weyers, R.E. Sprinkel, M.M, Anderson-Cook, C.M. 2002. Impact of specification changes on chloride-induced corrosion service life of bridge decks. *Cement Concrete Res* 32(8):1189–97.

Naïm, P. Wuillemin, P.H Leray, P. Pourret, O. & Becker, A. 2007. *Les réseaux bayésiens*, Eyrolles 3ème édition.

Nguyen, X.S. 2007. Algorithmes probabilistes appliqués à la durabilité et à la mécanique des ouvrages de génie civil. *PhD Thesis, INSA de Toulouse*.

Nguyen, M.T. 2011. Identification statistique de paramètres de diffusion dans le béton à partir de mesures. *M.Sc. Thesis, University of Nantes*.

Straub, D. der Kiureghian, A. 2010. Bayesian network enhanced with structural reliability methods: methodology. *J Eng Mech* 136(10):1248–58.

Tuutti, K. 1982. Corrosion of steel in concrete. *Swedish Cement and Concrete Institute*.

Vu, K.A.T. & Stewart, M.G. 2000. Structural reliability of concrete bridges including improved chloride-induced corrosion. *Structural Safety* 22:313–33.

Wallbank, E.J. 1989. *The performance of concrete in bridges: a survey of 200 highway bridges*. In: Mansell & Partners, editors. Department of Transport. London: HSMO.