Stochastic Evaluation of Carbonation Depth and Predictions Updating

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ABSTRACT

In the scope of the inspection plan optimization of civil engineering structures subject to carbonation (carbon dioxyde penetration), several analytical models help to predict the degradation evolution. The degradation model used here is coming from the european project DuraCrete. This paper investigates its predictive capability, using the *a priori* of its inputs given in the litterature, but also after updating its predictions based on simulated measures with a finite element code

KEYWORDS : *Carbonation, Updating, DuraCrete, Bayesian, Scarabett*

INTRODUCTION

Since the 19th century, the expansion of developed countries and the fast increase of their population has lead to the construction of numerous structures and infrastructures, in order to anwser to the needs in energy, in accomodations or in road and railway infrastructures. Those buildings, mostly built in reinforced concrete, are submitted to several degradation phenomenom that impair their integrity. However their importance implies that their safety is to be insured all the time, on account of economic and social matters. In order to assure the reliability level of those structures, they are regularly inspected and maintened according to IMR (Inspection, Maintenance and Repair) plans previously defined by the stakeholders. However by considering the global economic context, the costs induced by these operations call for a process optimization in order to reduce the long run monitoring cost.

Concerning reinforced concrete, several degradation type exist, such as concrete carabonation or chlorure ingress. Predicting the progression of these degradations is not an easy task in a probabilistic context where are included uncertainties in concrete characteristics and in environmental parameters which drive the degradation. It is mandatory to make them easily predictable by the stakeholders in a long run cost control context. These objectives are the key objectives of the ANR EvaDéOS project (Non destructive evaluation for the degradation prediction of structures and optimization of their monitoring), which began in late 2011. Numerous models exist to model with greater or lesser accuracy these degradation phenomenom. Two classes of models are distinguished, *(i)* the empirical analytical models and *(ii)* the complex models which use the finite elements method. The first class is the one that the stakeholders wish to use, so as to avoid a prohibitive computational cost and a too important need of data. However, if numerous analytical models exist, the knowledge of their predictions' accuracy concerning real structures is nonexistent.

The degradation predictions have as a final goal to optimize the inspection plan of an infrastructure. Those inspections give a direct measurement of the degradation state (the output of the degradation models) as well as the concrete characteristics. This information is to be used in order

to enhance the probabilistic predictions of the degradation models, using a bayesian formalism which considers the measurement errors inherent in the non destructive techniques.

The task 4 of the ANR EvaDéOS project has as a first objectif to identify and to rank the analytical models which are the most efficients, depending on the material data (porosity, compressive strength, etc ...) they need. The second objectif is to estimate the capability of the bayesian updating method to correctly enhance the degradation predictions, in presence or not of measurement noise, based on different inspection plans created according the stakeholders' constraints.

This paper presents the first results coming from the benchmarking of the models and the updating methodology. It is divided in five parts. The first one introduces the bayesian updating methodology used in the benchmarking context. The following section explains the generation of virtual carbonation data using a finite elements model. The third one presents the model used in the benchmarking, as well as the prior distributions available on is inputs, together with the several updating cases developed. The fourth part shows the results of this work. Finally, the last one concludes this study and mentions the different perspectives considered for the following of this benchmarking.

1. BAYESIAN UPDATING

Let $M(X,G,z,t)$ be a time dependant model function of the random vector X, the vector of deterministic parameters G (e.g.: model parameters which have been measured), indexed by the time t on different locations z of a structure.

The observed difference between the model prediction $M(X,G,z,t)$ and the observations Y^{obs} may come from [1] :

- an error vector of the model, denoted $\mathrm{E_{modele}}$, a priori unknown and calibrated by expert judgement as following a normal distribution $N(0,\sigma_{E_{modele}})$;
- an error vector of the observation measurement denoted $\mathrm{E_{mesure}}$, coming from the measurement technique.

Assuming that these errors are independant, we can thus define the global error vector such as $\mathrm{E_{glo}} \sim N\left(0,\sqrt{\sigma^2_{E_{mesure}}+\sigma^2_{E_{modele}}}\right)$. By writting that to each observation corresponds a global error realization, it comes

$$e_{glo}(z_p,t_q) = y(z_p,t_q) - M(x,g,z_p,t_q). \quad [1]$$

In a bayesian context, the likelihood of the global error according to the observations is thus written, under the assumption of independant measurements

$$L\left(\sigma_{E_{glo}},Y^{obs}\right) = \prod_{p=1}^{P}\prod_{q=1}^{Q}\varphi\left(\frac{M(x,g,z_p,t_q)-y(z_p,t_q)}{\sigma_{E_{glo}}}\right). \quad [2]$$

The vector of input parameters X is then an hyperparameters vector, with a posterior distribution explicited by

$$f_{X,\sigma_{E_{glo}}}(x,\sigma_{E_{glo}}) = \frac{1}{c}p_X(x)p_{\sigma_{E_{glo}}}(\sigma_{E_{glo}})L\left(\sigma_{E_{glob}},Y^{obs}\right). \quad [3]$$

In this paper, since the measurement errors are not considered, $\mathrm{E_{glo}}$ only contains the errors due to the model accuracy. Thus, the mean of the posterior distribution $\sigma_{E_{glo}}$ will be used as a ranking parameter for the degradation models.

2. VIRTUAL DATA GENERATION

In this study, it has been chosen to estimate the carbonation model capacities by confronting it to virtual data of carbonation depth simulated by finite elements (FE) in order to dispose of a data set the fullest possible.

The FE model is the SCARABET model [2]. In the futur, since the number of non destructive testing (NDT) achievable at a lesser cost will likely become important, 150 independant simulations have been made, from 3 correlated random variables:

- The concrete initial porosity (mean of 14% associated with a coefficient of variation of 15%) ;
- The intrinsic permeability of concrete (mean of $2.8 \times 10^{-17} m^2$ associated with a coefficient of variation of 25%) ;
- The initial quantity of portlandite (mean of $2890 kg/m^3$ associated with a coefficient of variation of 10%).

The impact related to the use of a lesser number of measuarements will be evaluated at a later stage. The others needed variables are the data of the concrete composition (given in the structure specifications), together with the relative humidity rate and the temperature which are given by real weather chronic. The modeled concrete is a C25. Its different properties are given in table 1.

Table 1 : Composition of the C25 concrete used - given by the structure specifications

Concrete composition (kg/m^3)		
	CEM I	295
	Sand 0/4	989
	Gravel 4/12	792
	Water	200
	w/c	0,68
Cement composition (%)		
Constituent	Clinker	96
	Secondary Constituent	4
Chemical characterisation	PAF	1,49
	SiO_2	20,29
	CaO	64,22

The output variables are profiles, evaluated each year during 60 years, of:

- Saturation Sr ;
- Porosity modified du to the carbonation ϕ ;
- Portlandite quantity.

The profiles' values are computed every 2mm over a 10cm depth. Since the carbonation models assume that the carbonation depth is clearly defined by a threshold, it is thus estimated from the portlandite quantity. We consider the concrete as carbonated as soon as 2/3 of the initiale portlandite quantity is consumed.

This arbitrary threshold, paired with the discretization scale of the profiles, unfortunately gives too discontinuous carbonation depth samples (every 2mm) in front of the magnitude of the simulated carbonation depths (between 0 and 10mm) and the accuracy of real measurements (magnitude of 0.1mm). In order to evaluate the potential influence of such a discretization scale on the updating process, it has been decided to compare the results obtained to the case where the profiles of portlandite are quadratically interpolated to simulate a *continuity* of the data. The results of such an interpolation

is shown 1, for one profile of carbonation at 30 years. It is clear that this interpolation is reasonable, since on the depths considered, the profile evolution shows a monotony easily interpolable. One has to be careful because the discretization scale resulting from this interpolation should not be too small. Indeed, the aim of this study is to estimate the prediction capabilities of the carbonation models, as well as the robustness of the updating process. The interpolation introduces a discretization scale which should not be smaller than the accuracy resulting from real measurements. Thus the interpolation made gives a profile's value every 0.1mm.

In order to stay coherent with the ANR EvaDéOS project, the profiles of saturation and porosity are not directly used since they are unattainable with any NDT. Instead, the mean of each profile over a 10mm depth is used, since this is realistic data that inspections are likely to provide.

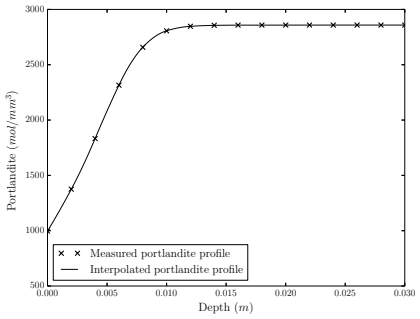


Figure 1 : Quadratic interpolation of a portlandite profile

3. DESCRIPTION OF THE BENCHMARKING

As a reminder, the aim of this benchmarking is to *(i)* rank the analytical models according to their accuracy in order to guide the stakeholders toward the use of the most accurate model they can use considering the data which are available, as well as *(ii)* to study the capability of the bayesian methodology at enhance the predictions of the models by using the data coming from an inspection (degradation state, material data).

3.1 Carbonation model

3.1.1 Introduction

Among the numerous analytical models of carbonation, four of them have been chosen by the ANR EvaDéOS projet according to their relevance regarding:

- their ease of use ;
- their very low computational cost ;
- the agreement between their inputs and the data measurable by NDTs (porosity, saturation rate, compressive strength, ...).

One model is selected in this study: the DuraCrete model [3].

3.1.2 The DuraCrete model

Deriving from the Brite EuRam III project DuraCrete [3], it is a empirical model of carbonation which considers that the phenomenon is dependent on

- the concrete composition ;
- the environmental conditions ;

- the curing conditions ;
- the age of the concrete.

Its analytical expression is

$$x_c(t) = \sqrt{\frac{2k_e k_c k_t C_{CO_2} t}{Rcarb}} \left(\frac{t_0}{t}\right)^n ; \quad [4]$$

Where

- $x_c(t)$ is the carbonation depth at time t (sec) ;
- k_e, k_c, k_t are factors which take into account the exposition conditions, the sort of cement, the curing conditions and the bias due to the calibration made through the use of accelerated conditions ;
- C_{CO_2} is the CO_2 concentration at the concrete surface, equals to $6.5 \times 10^{-4} kg/m^3$;
- t_0 is a reference time usually equals to 1 year ;
- n is an aging factor.

R_{carb} is defined as the quantity of carbonatable material. It depends on the concrete composition and follows

$$R_{carb} = 1000 * \frac{C_1 M_{CaO} V_p}{D_{CO_2}} ; \quad [5]$$

In which

- C_1 is the molar content of calcium coming from the AFm, AFt, et CH [4] ;
- C_2 is the molar content coming from the calcium silicate hydrate (C-S-H) gel [4].

It makes use of the diffusion coefficient of carbon dioxyde in concrete, which can be estimated from the empirical relation

$$D_{CO_2,A} = D_{CO_2,air} \phi^{4/3} (1 - Sr)^{10/3} ; \quad [6]$$

With

- ϕ is the concrete porosity, it can be estimated with an empirical relation if not measured [5] ;
- $D_{CO_2,air}$ is the diffusion coefficient of carbon dioxyde in the air equals to $1.39 \times 10^{-5} m^2/s$;
- Sr the saturation rate of concrete.

3.2 Prior distributions

The prior distributions used in this study are indexed in the table 2 They come from:

- the final report of the DuraCrete project [3] ;
- an expert judgement for the classical composition of a C25 concrete and of a CEM I cement.

The benchmarking also has simulations based on two others concretes, a C35 and a C45, which are not used in this paper. The priors of the porosity, the saturation rate and the global error are uniform distributions almost uninformative.

Table 2 : Prior distributions used with the DuraCrete model

k_e	$\sim$	$LN(\mu_{LOG} = -0.2, \sigma_{LOG} = 0.27)$		
k_c	$\sim$	$Beta(r = 1.86, t = 1.10, a = 0.35, b = 1.0)$		
k_t	$\sim$	$N(\mu = 0.983, \sigma = 0.023)$		
n	$\sim$	$Beta(r = 0.802, t = 1.30, a = 0, b = 0.5)$		
Ck	$\sim$	$U(a = 0.95, b = 1)$	LN	: Lognormal distribution
e/c	$\sim$	$U(a = 0.4, b = 0.6)$	N	: Gaussian distribution
c	$\sim$	$U(a = 280, b = 330)$	U	: Uniform distribution
CaO	$\sim$	$U(a = 0.64, b = 0.66)$	$Beta$	: Beta distribution
SiO_2	$\sim$	$U(a = 0.2, b = 0.21)$		
Sr	$\sim$	$U(a = 0.5, b = 1)$		
ϕ	$\sim$	$U(a = 0.01, b = 0.3)$		
$\sigma_{E_{glo}}$	$\sim$	$U(a = 1 \times 10^{-12}, b = 1)$		

3.3 Updating cases

According to the partners of the ANR EvaDéOS project, the most interesting predictions are either long-term (30 years) or short-terme(2 years). Severel updating cases have been developed in this context, of which two of them are used in this study, shown through table 3. Each case is handled in two ways:

- In the first one, the measurements of the porosity and of the saturation rate are used and thus included in the vector of deterministic parameters G. In this case, the prior distributions of the saturation rate and the porosity are updated in a second step ;
- The second one does not use these measurements. The prior distribution of the saturation rate is thus updated through the carbonation model. Since the porosity can be computed with an empirical formulation, its prior distribution is not used.

The updates are performed with an MCMC - Metropolis Hastings algorithm [6–8] giving 2000 points of the posterior distributions.

Table 3 : Updating cases

Case number	1st inspection	1st prediction at	2nd inspection	2nd prediction at
1	t^0 + 30 years	t^0 + 60 years		
2	t^0 + 30 years	t^0 + 32 years	t^0 + 38 years	t^0 +40 years

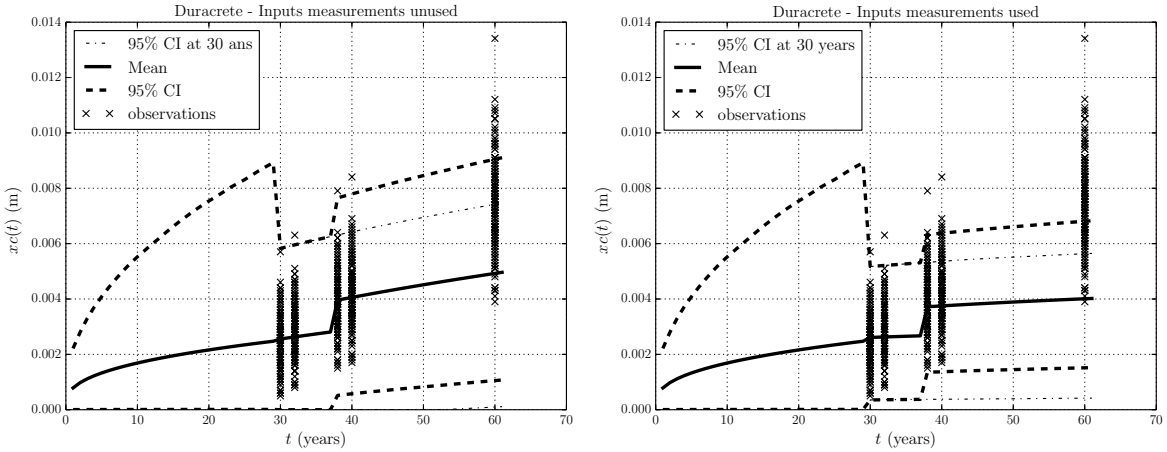
4. RESULTS

For the sake of clarity, the two updating cases (see table 3) are concatenated The figure 2a present the results obtained with the DuraCrete model when the observations of their inputs (concrete composition, saturation rate and porosity) are not used. The short-term predictive capabilities of the model (results compared to the observations at 32 years and 40 years) are similar and acceptable, the 95% confidence interval embraces all the data. This interval is narrower than the prior confidence interval. The updating contribution is thus not negligible. The long-term predictions (confidence interval estimated after the observations at 30 years) of the first updating plan are moderatly good since the corresponding confidence interval contains most of the observations at 60 years, yet is too large in its lower bound.

Table 4 : Global error $\sigma_{E_{glo}}$ estimated by the updating process with the DuraCrete model.

Updating date	Inputs measurements unused	Inputs measurements used
30 years	0.9 mm	0.7 mm
38 years	1 mm	0.7 mm

However, the mean tendencies clearly show that the kinetic of the model after the first update is not in agreement with the kinetic of the SCARABET model.



(a) (b)

Figure 2 : Results of the two updating plans. The observations corresponds to the carbonation depth computed with the SCARABET model.

The figure 2b presents the updating results when the known inputs of the DuraCrete model are used. The posterior confidence interval is narrower than in the previous case. The update seems much less efficient since the confidence interval does not contain all the observations used for the update. The current idea that could explain this phenomenom concerns how the saturation rate is taken into consideration. Indeed, in the SCARABET model the saturation rate only depends on the relative humidity for which only one weather chronic is available. Consequently there is no variability in the saturation profile computed for each sample. The update has therefore as an effect to give a posterior distribution for the mean of the saturation profile with a very low standard deviation, which is not any more representative of the temporal variability one may observe for this parameter. Moreover, the saturation rate is used to estimate the diffusion coefficient for the CO_2 which is one of the most influencing parameters of the model's kinetic. The very low standard deviation of the saturation rate thus reduces the width of the posterior confidence interval. One has to be cautious concerning the standard deviation of global error $\sigma_{E_{glo}}$ (see table 4) which wrongly indicates a better accuracy for this case. This criterion cannot be used without taking into consideration the shape of the confidence intervals.

CONCLUSION

In the context of the ANR EvaDéOS projet, we investigate the predictive capabilities of different carbonation models and the robustness of a bayesian updating methodology. Data computed by an efficient finite elements model are post-processed and used as references for the benchmarking of the

analytical models. Concerning the updating process, its robustness is confirmed if the data presents an acceptable continuity. The beginning of this benchmarking has shown some interesting results. The kinetic of the DuraCrete model is not satisfactory enough to have any confidence in the long-term predictions. However the short-term predictions appeared to be really efficient. The use of inputs measured has shown some limits. The model becomes too constrained and the predictions less reliable. The use of the saturation rate and the temperature as temporal processes instead of random variables is a perspective to enhance this result. The models will have to be changed since none of them is adapted to the use of changing environmental conditions. The others perspectives of this work are:

- an analysis of the results for different kind of concrete (C45 and C35) ;
- the use of three others carbonation models ;
- an extension to the chloride ingress degradation ;
- a confrontatio with *in situ* measurements.

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