Bayesian performance assessment of existing concrete structures combining different types of information from inspections and monitoring

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Abstract

When assessing existing concrete structures, adequate prediction of the time-dependent structural performance is crucial. Unfortunately, degradation processes are associated with large uncertainties and when executing additional investigations and measurements, significant model and measurement uncertainties play a dominant role in the reliability-based performance prediction. Bayesian updating provides a suitable engineering tool to adequately consider and combine available information for updating prediction models, enabling to make inferences which are difficult or impossible to make with traditional statistical approaches. Among others, uncertainties on degradation parameters and variables in structural reliability calculations can be updated based on combined information from measurements, monitoring, visual inspections and even quality control. Consequently, these updated uncertainties can be taken into account in full-probabilistic structural reliability calculations or partial factors for the structural verification can be adjusted according to the posterior probabilistic models in order to perform an instantaneous or time-dependent structural assessment. In this work, the Bayesian coupling of different types of information into the assessment process is explained, the predictive power of combined information is illustrated and particular challenges for future research developments are pointed out. Finally, an outlook is given on future engineering challenges to integrate such approaches further in the life-cycle assessment of existing structures.

Keywords: concrete structures, existing structures, assessment, Bayesian updating, monitoring, inspection, life-cycle assessment

1. Introduction

An increasing amount of the current activities in the construction sector are oriented towards the assessment of existing structures and the associated repair and upgrading interventions. The last decades significant progress has been made to analytically and numerically simulate the degradation process of concrete structures and their associated structural performance prediction in time. Nevertheless, whereas the phenomenon of corrosion is already quite well understood, structural engineers are challenged to deal with the large uncertainties involved. These can be uncertainties on the rate of corrosion, the exact initiation time, the amount of pitting, the spatial variation of corrosion along the structure, variations in concrete cover, the exposure to chlorides, etc.

For modelling the initiation period of corrosion, models can be found in (Duracrete, 2000; Lay et al. 2003). Probabilistic models for the variables in these models can be found in the *fib* Model Code for Service Life Design (*fib*, 2006) and *fib* Bulletin 76 (*fib*, 2015). Nevertheless, these models depend on the exposure class, concrete type and specific structural conditions. For existing structures, these are often unknown, because original drawings, specifications and/or calculation reports are missing. For modelling the propagation period on the other hand, there are no generally accepted models yet, as also illustrated by the wide range of models that can be found in literature. Degradation models are for example provided in (Alonso et al., 1988; Andrade et al., 1993; Coronelli and Gambarova, 2004; Duracrete, 1998; El Hajj et al., 2017; Hájková et al., 2018; Lay et al., 2003; Stewart and Rosowsky, 2002; Vu and Stewart, 2000). Examples of numerical simulations can be found in (Botte, 2018; Cavaco, 2009; Cavaco et al., 2013; Kagermanov & Markovic, 2022; Sanchez et al, 2010). The wide range of models is also accompanied by difficulties in defining appropriate distributions for the variables governing the degradation, again accompanied by a lack of information when assessing existing structures.

Besides this typical lack of information and the large uncertainties associated with the degradation processes, when executing additional investigations and measurements, significant model and measurement uncertainties play a dominant role in the reliability-based performance prediction. Efforts to generalize and internationally determine fixed values for parameters and probabilistic models for variables involved in the degradation process of existing concrete structures appear difficult to achieve. Hence, a solution to this problem is rather to be found in the application of Bayesian updating techniques that enable to take into account the specific situation of the structure and its environment, rather than aiming at the ambition to develop universal degradation models suitable for all structural typologies and environmental circumstances. Bayesian updating provides a highly adequate engineering tool to combine and fully exploit the power of combined available information, enabling to make inferences where classical statistical approaches fail.

The basic theory behind Bayesian statistics (dating already from 1763 with the famous paper (posthumously published) by the reverend Thomas Bayes (Bayes M., Price M., 1763)) focused on solving the question how to assess the probability of a certain value of not observable quantities, given a set of related measurements. Note that this is exactly the challenge often faced with in the assessment of existing structures, where inferences need to be made on parameters or properties which cannot be measured directly (strength, stiffness, chloride-ingress, corrosion degree, etc.), and indirect information needs to be used instead (visual inspection, crack measurements, vibration measurements, strain measurements, deflection measurements, etc.). However, it is only the last decennia that the Bayesian point of view is used extensively due to the advances in computational abilities and the development of more efficient numerical algorithms to solve the mathematical difficulties associated with Bayesian statistics. Although already common practice to tackle research challenges, the methodology has still not yet fully found its way into practical applications by practitioners in civil engineering, where frequentistic approaches still dominate statistical inference to deal with uncertainties.

2. Background

Approaches applied in current engineering practice are most often based on model updating, where the unknown parameters (e.g., stiffness of the structure) are assumed to be fixed instead of modelled with random variables. The parameters are adjusted until the model fits the experimental data, sometimes accompanied by a confidence interval on the resulting values. Examples of such model updating can be found in (Abedin et al., 2022; Bertola et al., 2022; Fritzen et al., 1998; Padil et al., 2020). Bayesian assessment on the other hand, due to the modelling with random variables, provides a posterior distribution of the parameters of interest. As such, it also accounts for errors in the measurements and in the model. The most probable value of the variable of interest can be derived, together with the corresponding uncertainty. Moreover, whereas in current practice mostly the stiffness of a model is adjusted to represent damage, Bayesian inference can be applied in such a way that also the variables in the underlying degradation mechanism are inferred. However, a challenge ahead is to make the Bayesian way of thinking more accessible.

Focussing on single sources of information, Bayesian theory has frequently been employed to update bridge resistance and reliability using observed and historical data (e.g., Geyskens et al. 1998, Zheng and Ellingwood 1998). Often, direct measurements of the quantity of interest are used in a Bayesian updating framework. For instance, Enright and Frangopol (1999) and Marsh and Frangopol (2008) utilize direct measurements of the corrosion rate to enhance the accuracy of reliability estimates. Ma et al. (2013) directly measure variables of interest, updating distributions based on field inspection results of concrete strength and cover, while updating the distribution of corrosion loss through destructive measurements. Faroz et al. (2016) conducted Bayesian updating of steel loss, assuming the existence of a non-destructive tool capable of measuring steel loss in concrete.

Information about updating variables in time-dependent corrosion models using indirect and non-destructive data, such as strains and modal data, is however rather scarce in literature. Strauss et al. (2008) for example fit a prediction function to SHM (Structural Health Monitoring) data and then update it based on monitored data. Heitner et al. (2016) update the general remaining reinforcement section using deflection-based damage indicators. Li and Jia (2020) used complete and incomplete inspection data for Bayesian updating of bridge condition deterioration models. Further, updating and calibration of deterioration models for reinforced concrete structures in a Bayesian context has been investigated by e.g., Faroz et al. (2016) and Gu and Li (2020). A sequential Bayesian updating approach for time-variant reliability analysis of ageing structures has been presented in Alam et al. (2023).

The present work is an extended version of a recent conference paper (Caspeele and Botte, 2023). Considering the scarce and rather scattered information about the application of Bayesian updating based on indirect and combined information, in the following an overview is provided on recent research focussing on updating performance prediction and reliability-based assessments taking into account different types as well as multiple sources of information. This research covers different main knowledge gaps in current literature, as discussed above. One of the main advances in the discussed researches is the use of indirect information in the assessment of damage, such as data from ambient vibration tests and from static load tests. This data is not used to update the damage of the structure by modelling a stiffness reduction, but by really updating the corrosion degree (i.e., remaining steel section) or the remaining prestress. In these researches, it has also been illustrated how not only corrosion can be inferred, but also how Bayesian assessment can be used to update distributions of the variables in the degradation models, such as initiation period and corrosion rate. This is an important step forward as it allows not only to assess the resistance at the time of inspection, but also leads to more accurate predictions of the future degradation and hence of the remaining service life of the structure. As such, more informed preventive maintenance can be applied to the structure instead of only reactive maintenance. Finally, the mentioned researches also illustrated the strength of Bayesian inference when combining different types of data. Not only data from different tests are incorporated, but it is also illustrated how the information from visual observations can be included.

After revisiting some basics on Bayesian approaches, in the following sections it is explained and illustrated how Bayesian updating techniques are of added value in the assessment process. Variables in structural reliability calculations can be updated on the basis of direct as well as indirect measurement data. Sources of information contained in different types of measurements or even visual inspections can be combined in order to make much more informed inferences and to reduce uncertainties in the reliability-based performance assessment, compared to when such data is analysed separately. It is also explained how degradation models whose parameters generally are difficult to find consensus about, can gradually be updated when more information becomes available. Even, although often forgotten, the positive effect of quality control can be taken into account when assessing the structural reliability. After updating the uncertainties of the variables involved, these posterior distributions can be taken into account in full-probabilistic structural reliability calculations, or partial factors used in semi-probabilistic assessment approaches can be adjusted on the basis of updated uncertainties (*fib* 2016, *fib* 2024). Finally, also an outlook is given to future challenges to integrate such approaches further in the life-cycle assessment of existing concrete structures.

It should be pointed out that the purpose of this work is not to provide an extensive overview of all relevant research in the field of performance assessment of existing structures based on Bayesian inference. The main focus of this paper is to illustrate how Bayesian updating techniques can contribute greatly to objective assessment and decision-making with respect to the management of existing structures. Nevertheless, a critical note will also be made on the gap between the current research efforts and the integration of Bayesian assessment approaches in civil engineering offices.

3. Bayesian updating revisited

The Bayes' theorem to calculate the probability P of an event E_i given the observation A (i.e., the posterior probability of E_i) is given by:

$$P[E_i|A] = \frac{P[A|E_i]P[E_i]}{P[A]} \tag{1}$$

where $P[E_i|A]$ is called the posterior probability of E_i, $P[A|E_i]$ is often referred to as the likelihood (i.e., the probability of observing a certain outcome given a certain cause) and $P[E_i]$ is called the prior probability of the event E_i (i.e., prior to the knowledge about event A). Hence, Bayes' theorem enables to update probabilities, based on new information. In case of continuous distributions, the continuum formulation of Bayes' theorem can be used. Consider a random variable X which has a probability density function $f_X(x|\boldsymbol{\theta})$ depending on a parameter vector $\boldsymbol{\theta}$. In case new information becomes available, the prior distribution function $f'_{\boldsymbol{\Theta}}(\boldsymbol{\theta})$ of the parameters $\boldsymbol{\theta}$ can be updated towards a posterior distribution function $f''_{\boldsymbol{\Theta}}(\boldsymbol{\theta})$ (Gelman et al. 2004):

$$f_{\boldsymbol{\Theta}}''(\boldsymbol{\theta}) \equiv f(\boldsymbol{\theta}|\boldsymbol{I}) = \frac{L(\boldsymbol{\theta}|\boldsymbol{I})\cdot f'_{\boldsymbol{\Theta}}(\boldsymbol{\theta})}{\int L(\boldsymbol{\theta}|\boldsymbol{I})\cdot f'_{\boldsymbol{\Theta}}(\boldsymbol{\theta})d\boldsymbol{\theta}} = c \cdot L(\boldsymbol{\theta}|\boldsymbol{I}) \cdot f'_{\boldsymbol{\Theta}}(\boldsymbol{\theta}) \tag{2}$$

where c is a normalizing constant, $L(\boldsymbol{\theta}|\boldsymbol{I})$ is the likelihood function, i.e., the likelihood of the parameters $\boldsymbol{\theta}$ based on the new information $\boldsymbol{I}$. Assume for example that n independent results x_i are observed, then the likelihood associated with this new information is given by the probability:

$$L(\boldsymbol{\theta}|\boldsymbol{I}) \equiv L(\boldsymbol{\theta}|x_1, \dots, x_n) = \prod_{i=1}^{n} f_X(x_i|\boldsymbol{\theta}) \quad (3)$$

In case of correlated observations, the likelihood can be extended to a multivariate distribution including the correlation between variables.

In contrast to the classical or frequentistic approach (Cox, 2006; Neyman, 1937), prior information can be taken into account through the prior density function of the parameters, i.e., $f'_{\boldsymbol{\Theta}}(\boldsymbol{\theta})$. The way in which this influences the posterior density function is depending on the relative importance of the prior information compared to the new information (i.e., the likelihood function). In order to *let the data speak for themselves* most often non-informative or vague priors are used, which maximize the information provided by the likelihood function (see e.g., Box & Tiao 1973; Gelman et al. 2004). The difference between the Bayesian approach and the classical or frequentistic approach is explained clearly in for example (Simoen, 2013; Wagenmakers et al., 2008).

When calculating the posterior distribution, computational difficulties arise due to the necessary evaluation of high-dimensional integrals. This was the main obstacle for the use of Bayesian methods in the previous century. Together with the advances in computational efficiency, a group of so-called Markov Chain Monte Carlo methods (MCMC) were developed (see e.g., Gelman et al. 2004) for the numerical determination of the posterior probabilities. These have for example been applied in (Beck & Au, 2002; Hastings, 1970; Ranjan et al., 2021) A comparative study of different MCMC algorithms has been presented in Jin et al. (2019), where different adaptive MCMC algorithms are reviewed and compared. These adaptive algorithms try to relieve the difficulty of the usual trial-and-error approach to tune and select the optimal proposal mechanism to be applied in the MCMC sampling. Besides the adaptive algorithms discussed in (Jin et al., 2019) (DRAM, DREAM and AHMC algorithm), another development is the use of Transitional

Markov Chains (TMCMC), as for example discussed in (Betz et al., 2016). Other approaches for Bayesian inference are the use of subset simulation, as for example applied in (Betz et al., 2018; Wang and Shafieezadeh, 2020).

4. Application of Bayesian updating techniques in the assessment of existing concrete structures

The assessment process commonly consists of several steps, encompassing condition assessment, performance prediction, monitoring, performance updating and an optimization of interventions (Figure 1). Uncertainties are involved in all of these steps, and Bayesian updating can play a role in each of the steps to adjust lacking knowledge when more information becomes available as well as providing indirect information for other steps in the assessment process. In particular, parameters that are difficult to be fixed in general (e.g., degradation parameters such as diffusion coefficients and carbonation resistance, environmental conditions, direct and indirect costs, etc.), can be updated when more information becomes available and as such bypass the often-occurring conundrum when trying to fix model parameters in general for all situations. Moreover, while often forgotten, also the interaction between the different steps in the assessment process plays an important role when updating uncertainties and the combination of this kind of information can lead to a significant improvement of the posterior uncertainties. Monitoring data can for example also be used to update degradation models used in the condition assessment. Structural analysis models can be extended by random fields that enable to update the state of degradation and the associated spatial variability – which is often not quantitatively accounted for – when test and monitoring data becomes available.

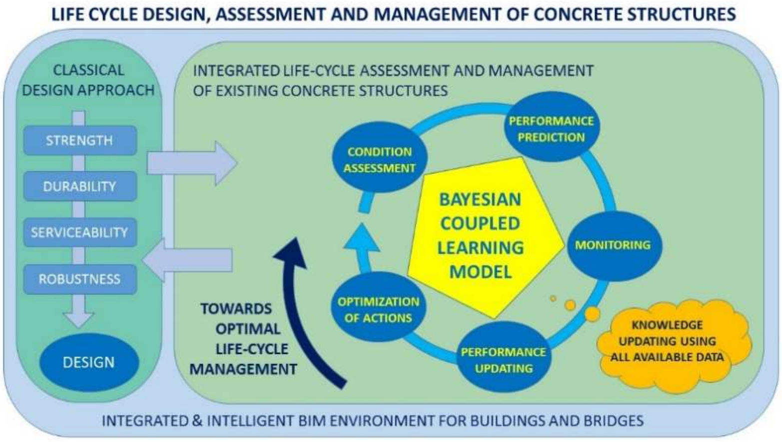


Figure 1: Principle of life-cycle design, assessment and management of concrete structures and the place of Bayesian approaches to update within and in-between all components of the assessment process.

In the following, several more specific aspects on how to exploit Bayesian updating in the framework of assessment of existing concrete structures are highlighted, in particular considering updating on the basis of the following sources of information:

- direct measurements of material properties, geometry, etc.
- in-situ static load tests
- laboratory static load tests
- ambient vibration data
- visual inspections

Subsequently, the use of Bayesian updating for calibrating degradation models for concrete structures is explained as well as the Bayesian updating based on information from quality control.

4.1. Updating variables involved in structural reliability calculations

4.1.1. Updating of variables on the basis of direct associated measurements

Bayesian updating methods based on prior information are already widely applied for the assessment of existing concrete structures (see e.g., Enright and Frangopol, 1999; Giannini et al., 2014; Jacinto et al., 2014; Strauss et al., 2008). In case of the assessment of concrete strength, quantitative prior knowledge on concrete strength distributions can be found in literature (see e.g., Rackwitz 1983), and similarly for other variables (see e.g., JCSS 2001). Prior information can for example be modelled based on normal-gamma or lognormal-gamma distributions. These types of distributions are natural conjugate priors for updating the mean and standard deviation of the normal or lognormal concrete strength distribution, which enables to find simple analytical expressions for updating the parameters of the strength distribution function in a Bayesian framework, such as for example available in ISO2394:2015. When for example the characteristic concrete strength has to be estimated from a limited number of test samples, the use of a combined vague-informative prior is of particular interest (Caspeele & Taerwe, 2012). Prior knowledge on the standard deviation can be taken into account, leading to a reduction in the standard deviation of the predictive strength distribution and a more realistic estimation of the characteristic concrete strength in cases where only a limited number of test results are available.

A similar approach can be followed for other variables, such as degradation parameters. For example, Marsh & Frangopol (2008) use corrosion rate sensor data to improve the accuracy of reliability estimates of the corrosion rate and Ma et al. (2013) use field inspection results of concrete strength and cover to update their respective distributions and update the distribution of the corrosion loss based on destructive measurements of this parameter. Faroz et al. (2016) performed Bayesian updating of the steel loss assuming that there exists a non-destructive tool that is capable of measuring steel loss in concrete. Since such tests, i.e., directly measuring the variable of interest, are not always available, it is interesting to also consider Bayesian inference based on indirect test data, such as data from load tests or ambient vibrations. Bayesian assessment based on these data types will be discussed in the following sections.

4.1.2. Data from in-situ static load tests

Data obtained from static load tests provide indirect information on variables affecting the behaviour of the structure to these tests. For example, the stiffness of the structure will affect the deformations under applied loads. The stiffness is in turn affected by degradation. Hence, data from static load tests can be used to indirectly update the probabilistic distributions of variables which are of significant importance when assessing the behaviour of concrete structures by means of an analytical or numerical model. Such static load tests can be executed in situ on (part of) the structure or in laboratory on representative elements which have been taken from the structure to be assessed. In such cases, the observed data $\overline{\boldsymbol{d}}$ can according to (Simoen et al., 2015) be written as:

$$\overline{\boldsymbol{d}} = \theta_{\mathrm{M}} M(\boldsymbol{\theta}) + \boldsymbol{\eta} = \theta_{\mathrm{M}} M(\boldsymbol{\theta}) + \boldsymbol{\eta}_G + \boldsymbol{\eta}_D \tag{4}$$

where, $M(\boldsymbol{\theta})$ is a model with input parameters $\boldsymbol{\theta}$ used to predict the data $\overline{\boldsymbol{d}}$, θ_M is the model bias, $\boldsymbol{\eta}$ is the prediction error consisting of a modelling error $\boldsymbol{\eta}_G$ and the measurement error $\boldsymbol{\eta}_D$. Assuming a normal distribution with zero mean and covariance matrices $\boldsymbol{\Sigma_D}$ and $\boldsymbol{\Sigma_G}$ for the latter, the likelihood can be expressed as:

$$L \sim (\det(\boldsymbol{\Sigma_D} + \boldsymbol{\Sigma_G}))^{1/2} \exp\left(-\frac{1}{2} F_{ML}\right) \tag{5}$$

where F_{ML} is the maximum likelihood function, which can be formulated as:

$$F_{ML} = \left(\theta_{\mathrm{M}} M(\boldsymbol{\theta}) - \overline{\boldsymbol{d}}\right)^T (\boldsymbol{\Sigma_D} + \boldsymbol{\Sigma_G})^{-1} \left(\theta_{\mathrm{M}} M(\boldsymbol{\theta}) - \overline{\boldsymbol{d}}\right) \tag{6}$$

When looking into the incorporation of information of monitoring data based on static load tests on infrastructure, the approach followed in (Vereecken et al., 2024b) illustrates the possibility to use the data of strains and displacements collected during a static load test on a reinforced concrete slab bridge in Amsterdam (The Netherlands) to update the spatial distribution of the stiffness of the deck along the bridge (Figure 2). In case of measurement of strains and considering $\boldsymbol{\Sigma}_{\boldsymbol{G}} = \mathbf{0}$, the likelihood function can be rewritten as (Vereecken et al. 2022):

$$F_{ML} = \sum_{j=1}^{N} \frac{1}{\sigma_{\varepsilon}^{2}} \left(\bar{\varepsilon}_j - \varepsilon_j(\boldsymbol{\theta})\right)^2 \quad (7)$$

where N is the number of measurements, σ_{ε} is the standard deviation of the measurement error, $\bar{\varepsilon}_j$ are the measured strains and $\varepsilon_j(\boldsymbol{\theta})$ are the strains obtained from a numerical model with input parameters $\boldsymbol{\theta}$. However, in order to arrive at the posterior model important choices have to be made, among others in relation to the model error and possible spatial correlation of parameters. Unfortunately, information in relation to these choices is very scarce in literature, as well as a lack of suitable data exists to validate choices with respect to model uncertainties and models for spatial variability. In (Vereecken et al. 2024b), the influence of these parameters was investigated to determine the best posterior model for an actual engineering structure, based on MCMC in combination with surrogate modelling to limit the computational cost. Therefore, different models for the prediction error, as in (Simoen et al., 2013), the model bias, and different definitions of the stiffness of the structural model were considered in the parametrization of the physical and statistical models. Two situations were considered, i.e., in *situation* 1 the bridge was modelled with only one uncracked and one cracked stiffness, whereas in *situation* 2 a stiffness model for the bridge was adapted with different stiffnesses at supports and spans. The different cases considered with respect to the prediction error and the model bias are summarized in Table 1. Bayesian-based model selection was performed both based on log evidence and posterior predictive capabilities in order to evaluate how well they correlate and convey the same message.

Table 1: Different cases considered for model bias and prediction error.

Case	**Model bias**		**Prediction error type**	**N° of inferred parameters sit. 1***	**N° of inferred parameters sit. 2***
	Type	**Data-points dependence**			
1	No model bias	/	Deterministic σ_η	2 + 0 = 2	17 + 0 = 17
2	No model bias	/	Uncertain σ_η	2 + 2 = 4	17 + 2 = 19
3	Same for all data-points	Fully correlated	Deterministic σ_η	2 + 2 = 4	17 + 2 = 19
4	Different for each data point	Correlation matrix	Deterministic σ_η	2 + 3 = 5	17 + 7 = 24
5	Same for all data-points	Fully correlated	Uncertain σ_η	2 + 4 = 6	17 + 4 = 21

* Total number of inferred parameters = number of stiffnesses considered + number of parameters for model bias and prediction error

The posterior distributions of the stiffness along the deck of the bridge are illustrated in Figure 2 for two models: one adopting two possibilities for the stiffness (cracked and uncracked – *situation 1*) and one adopting for more flexibility in the stiffness distribution along the length (*situation 2*). The results are provided for the five cases described above. A more flexible model for the stiffness distribution was found to be preferred over a model allowing less spatial variability. Furthermore, an improved accuracy was obtained by including spatial variability in the model bias. However, the advantage was found to be limited over the required additional effort, i.e., the additional accuracy being masked by a lower precision due to the additional uncertainties introduced by the larger number of parameters to be estimated. The work performed in (Vereecken et al. 2024b) hence illustrates that, when applying Bayesian inference based on static load data to real-case structures, if the calibrated model is to be used for performance prediction, the performance of different candidate models should be compared before a model (and corresponding parametrization) is selected or rejected.

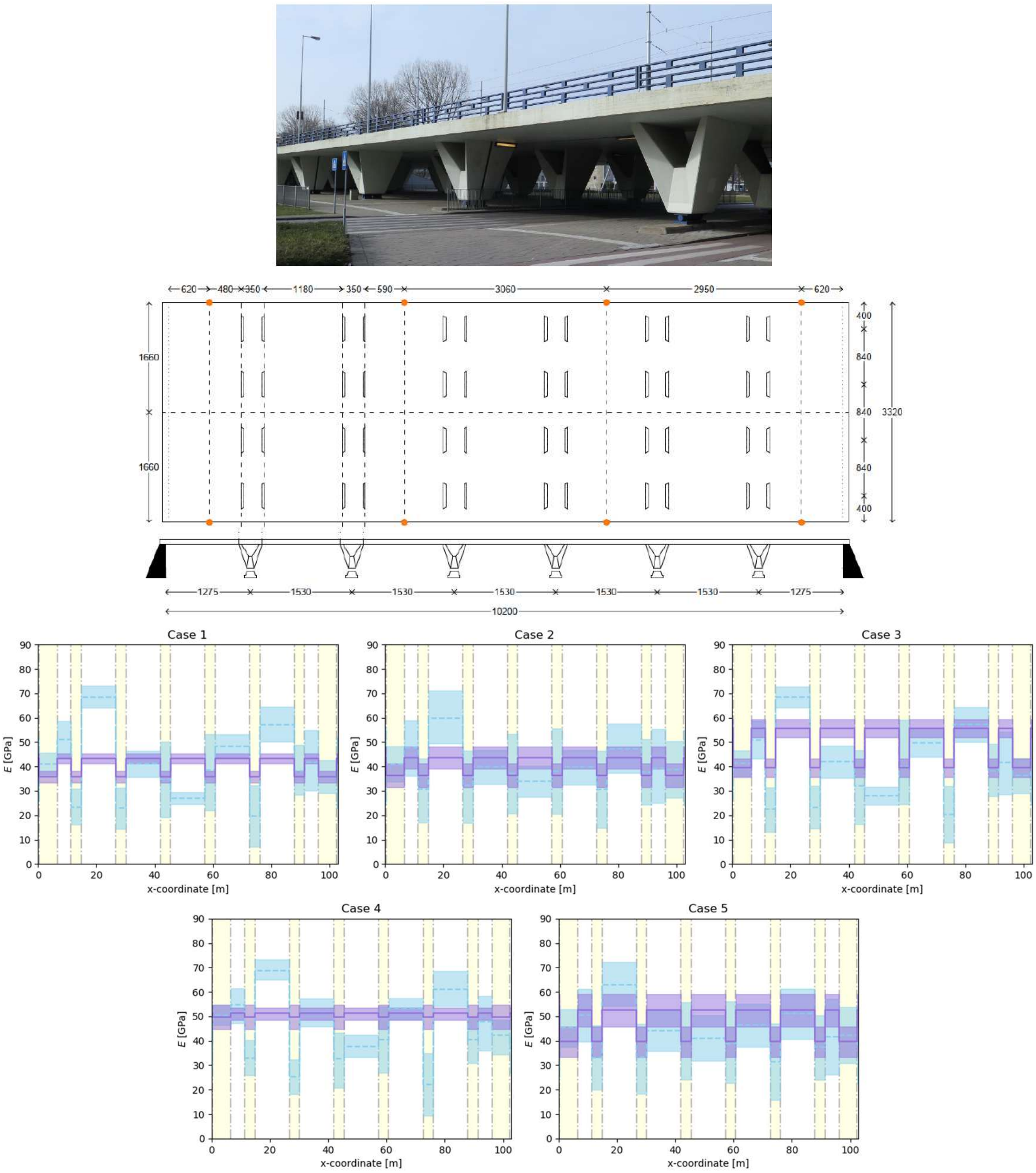


Figure 2: Picture, top and side view of bridge 705 with its main dimensions in [cm] (Rozsas et al., 2022) and posterior distributions of the stiffness along the deck for two *situations:* two discrete stiffness distributions (dark/purple) and a spatially variable stiffness distribution (light/blue). The solid/dashed line represents the posterior mean, and the hatched area represents the posterior 90% highest density interval (HDI) (Vereecken et al., 2024b).

4.1.3. Data from laboratory static load tests

Bayesian updating can also play a significant role when analysing results from a limited number of (e.g., large-scale) tests. In this regard, the approach developed in (Botte et al., 2021) is of particular interest, adopting a two-step Bayesian framework in combination with non-linear finite element modelling in order to assess the remaining prestress and associated uncertainties in post-tensioned concrete beams from the 1940's. In the first step, the distributions of material characteristics such as the compressive strength, tensile strength, Young's modulus and density of concrete as well as the Young's modulus of the prestressing steel were updated using MCMC and based on direct measurements of those properties. Prior information was selected from the JCSS Probabilistic Model Code (JCSS 2001) based on historical documentation regarding the design. Considering these updated distributions for the material properties, a vague prior distribution of the remaining prestress was consecutively updated based on the information obtained from large-scale load tests in the laboratory. In particular the cracking moment (corresponding to the load P_{cr}), moment of reopening of cracks (corresponding to the load P_0) and behaviour in the non-linear branch of the load-displacement diagram (corresponding to the load P_δ) contain in that regard very valuable information, since these depend significantly on the remaining prestress level. An overview of this updating approach is presented in the flowchart in Figure 3.

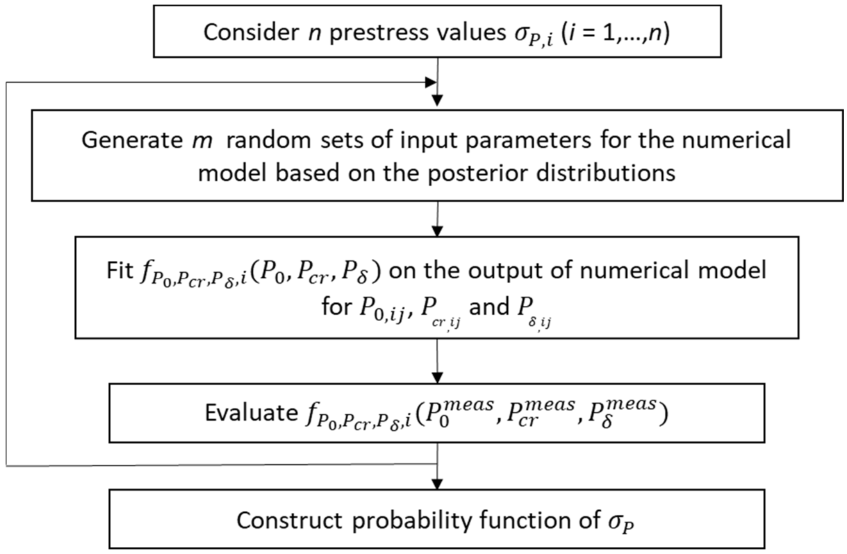
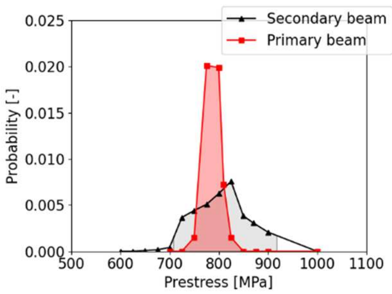


Figure 3: Flowchart of updating approach for the remaining prestress level σ_P.

In this case study, only two beams of a whole roof structure were tested (two types, i.e. a primary and a secondary beam). To not only get information on these two specific beams, but to be able to gain information on the remaining prestress in the whole roof structure, the updating of the remaining prestress in this study was not achieved by standard MCMC procedures. An adjusted Bayesian inference procedure was applied to be able to account for the possible variations between similar beams in the same structure (which are not tested). If multiple similar tests would be performed on the roof structure, these could have induced varying measurement results. Hence, this uncertainty was also accounted for when performing the Bayesian updating procedure. The main advantage of the Bayesian analysis over a deterministic analysis altering the remaining prestress in a finite element model until it fits the measurement results, is the quantification of the uncertainty on this prestress, enabling to make more informed inferences. As can be seen in Figure 4, this is still quite large for one of the tested beam types, which can be attributed to the relatively large measurement errors and the larger intrinsic uncertainty originating from the uncertainty of the input parameters for this beam type.

(a)

(b)



(c)

Figure 4: (a) Static load test on a secondary beam, (b) Primary beam after failure, and (c) the posterior distribution of the remaining prestress including the 90% HDI.

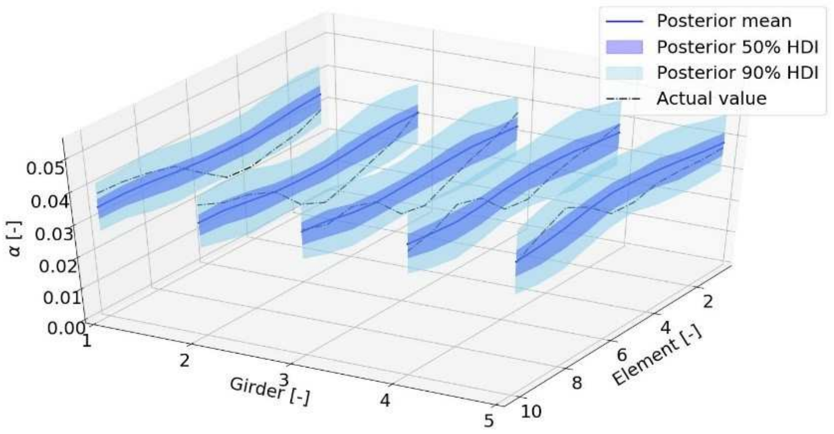
4.1.4. Ambient vibration data

Model-based structural health monitoring is often executed through vibration-based finite element model updating. It is based on the assumption that local structural damage results in a local reduction of stiffness. The presence of damage can be detected, located and quantified (Simoen et al., 2015). The natural frequencies identified in a modal test only provide global information, whereas localization of damage requires the identification of mode shape displacements. However, mode shapes are usually characterized by a larger identification uncertainty, and they are not extremely sensitive to moderate changes in structural stiffness (Simoen et al., 2015). Hence, additional properties can be measured which are more sensitive to changes in stiffness, such as modal flexibilities (Catbas et al., 2008), modal curvatures (Pandey et al., 1991) and modal strain energies (Jaishi & Ren, 2007). In case eigenvalues and mode shapes are used in a Bayesian model updating procedure and considering $\boldsymbol{\Sigma}_{\boldsymbol{G}} = \mathbf{0}$, the likelihood function can be written as:

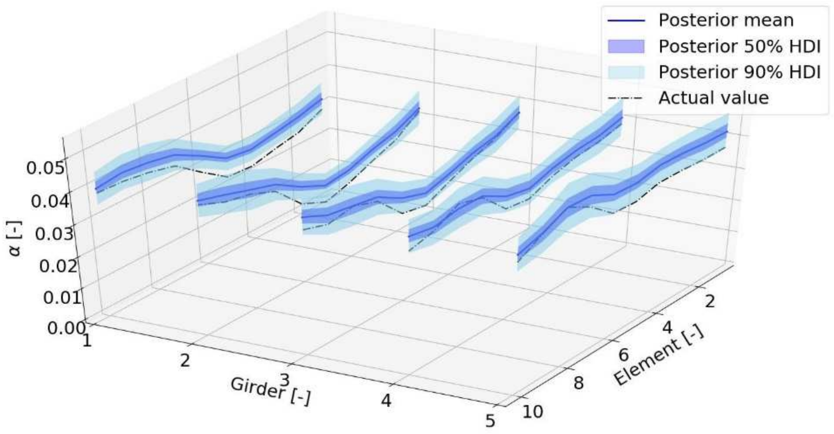
$$F_{ML} = \sum_{j=1}^{N} \frac{\left(\bar{\lambda}_j - \lambda_j(\boldsymbol{\theta})\right)^2}{\sigma_{\lambda,j}^2} + \sum_{j=1}^{N} \frac{\left(\bar{\phi}_j - \phi_j(\boldsymbol{\theta})\right)^2}{\sigma_{\phi,j}^2} \tag{8}$$

where N is the number of modes considered, $\bar{\lambda}_j$ and $\bar{\phi}_j$ are the measured eigenvalues and mode shape vectors and $\sigma_{\lambda,j}^2$ and $\sigma_{\phi,j}^2$ are the standard deviations of the error related to the measured frequency and mode shape respectively.

In (Vereecken et al. 2022), it is illustrated how measurement data from ambient vibration tests can be used to update the distribution of the corrosion degree of a reinforced concrete structure. Corrosion influences the stiffness and a reduction in stiffness affects the behaviour under dynamic loading. By assigning random fields to the variables in the corrosion models, also the spatial distribution of the corrosion degree can be accounted for. In Figure 5 it is illustrated how, for a reinforced concrete girder bridge with 5 girders, each subdivided in 10 elements along their length, regions with a higher corrosion degree can be localized based on data from ambient vibration tests. It can be seen how the posterior distribution of the corrosion degree shifts towards higher values in more corroded regions.



(a)



(b)

Figure 5: Posterior distribution of the corrosion degree of an RC girder bridge after Bayesian inference based on (a) natural frequencies and displacement mode shapes of the first four modes; (b) modal strains from the same modes

4.1.5. Visual inspections

Visual inspections are the most frequently occurring types of inspections since these are relatively simple to execute. These inspections provide rough indications whether there is a risk related to human safety or whether there are any alarming time-dependent evolutions in the structural behaviour. Although often forgotten, they provide an undeniable advantage when performing Bayesian updating in relation to assessment of existing concrete structures, as they enable to significantly reduce the large uncertainties involved in the corrosion initiation prediction. Regarding corrosion, the most important visual observations are the presence of rust stains, corrosion cracks or concrete spalling. If any of these signs are present, it can be concluded that the reinforcement at that location has started to corrode. In Figure 6 it is illustrated how visual observations can influence the distribution of the initiation period. If at t_{insp} it is observed that rust stains are present, the initiation time T_i should be lower than t_{insp}. Hence, the distribution of the initiation time can be updated as follows (Botte, 2017):

- In case inspection reveals that corrosion has initiated at some point in time before t_{insp}:

$$F''_{T_i}(t) = \frac{F'_{T_i}(t)}{F'_{T_i}(t_{insp})} \tag{9}$$

- In case inspection reveals corrosion has not yet initiated at t_{insp}:

$$F''_{T_i}(t) = \frac{F'_{T_i}(t) - F'_{T_i}(t_{insp})}{1 - F_{T_i}(t_{insp})} \tag{10}$$

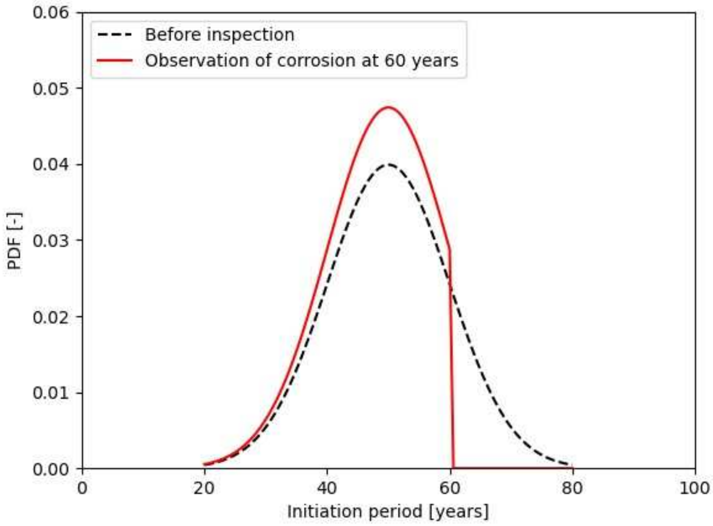


Figure 6: Influence of a visual observation of corrosion on the PDF of the initiation period.

In addition, this visual data can be used to supplement the static and/or dynamic data as it – through the application of the Bayesian updating approach – can lead to inferences on the origin of the stiffness reduction. Furthermore, models to predict the crack width or time to cracking can be updated based on the observed crack locations or crack widths according to the approach (cf. infra). It should however be pointed out that visual inspections can also suffer significantly from operator bias. If such bias is present, this bias should and can be accounted for within the Bayesian framework when evaluating the information from the visual inspections, although adequate data in relation to probabilistic models and their associated parameters about such bias is currently lacking in literature.

4.1.6. Combining different sources of information

Each of the mentioned test methods and corresponding data types has its advantages and limitations. Nevertheless, in a Bayesian context, the different types of data can be combined in order to optimize the assessment procedure. A possible solution consists of first localizing the critical elements of the structure based on the modal data so that these can be prioritized when strain data are collected under proof-loading. Combining the data of both measurements will lead to reduced identification uncertainties when compared to the case where the measurements are considered separately. An illustration of the advantage of combining both sources of information is provided in Figure 7 in relation to the corrosion degree assessment in a bridge system consisting of 5 girders, considering model data from vibration measurements, strain measurements and the combination of both. In (Vereecken, 2022) the advantage of updating on the basis of combined information with or without the information from visual observations is illustrated in relation to the posterior distribution of the corrosion degree of reinforcement in a concrete beam (see Figure 8). As can be seen, although often forgotten to take into account information from visual inspections, the reduction in uncertainty is considerable when taking into account the appearance of rust products.

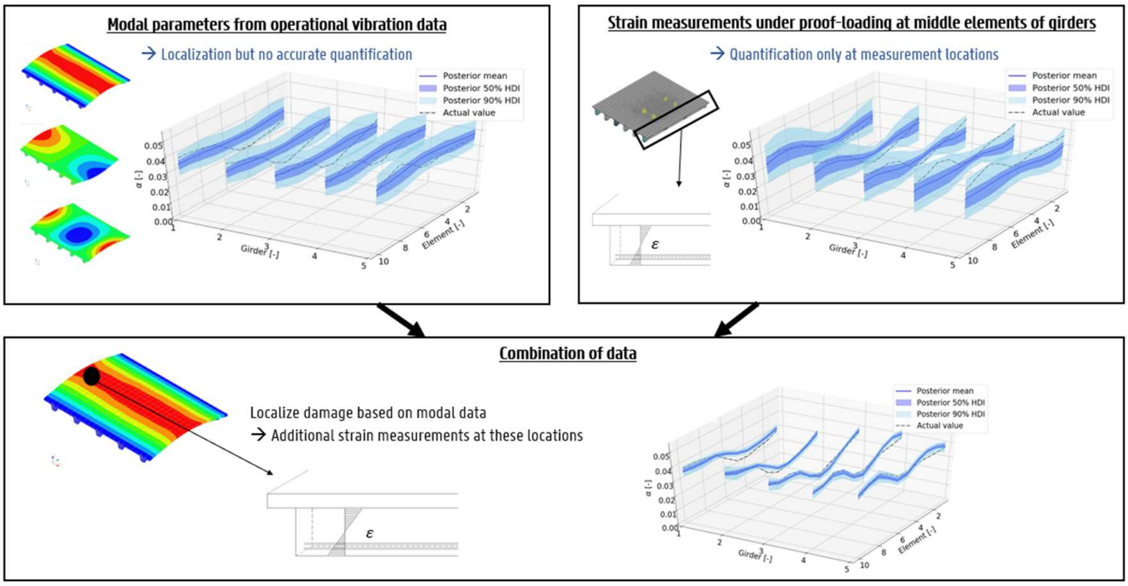
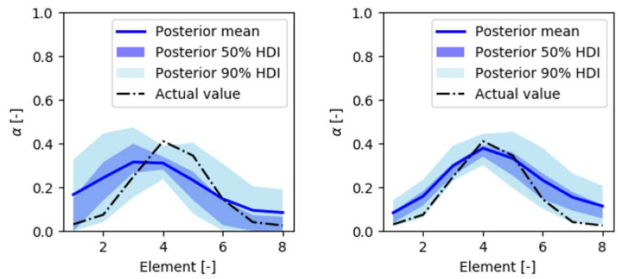


Figure 7: Illustration of updating the corrosion degree based on strain data from proof-loading and modal data from ambient acceleration measurements and the improved predictability considering both sources of information.



(a) (b)

Figure 8: Posterior corrosion degree of a simply supported beam when measuring the strains under proof loading (a) without visual observation, (b) with visual observation of rust stains. For more detailed information, see (Vereecken 2022).

Also, in (Vereecken et al., 2024a), the influence of taking into account information from visual inspections in the definition of the prior distributions of corrosion variables is illustrated. The more informative the prior, the better the actual representation of the corrosion degree. However, this effect is less noticeable if the measurements themselves already contain a lot of information. Furthermore, it is important that the models used in the Bayesian inference resemble the actual situation as good as possible. Nevertheless, care should be taken in defining prior distributions based on visual observations when combining with other measurement information. When the prior becomes too narrow or is based on wrong assumptions, it can push away the posterior distribution from the actual measurement result as illustrated in Figure 9. The latter figure illustrates the effect of different prior distributions on the posterior distribution of the corrosion degree based on static strain measurements. Three different prior distributions were considered: (i) a vague prior distribution, uniform between 0.05 and 0.30; (ii) an informative prior defined based on a visual observation of the average crack width and (iii) an informative prior distribution based on a visual observation of the maximum crack width. For more detailed information, see (Vereecken 2022).

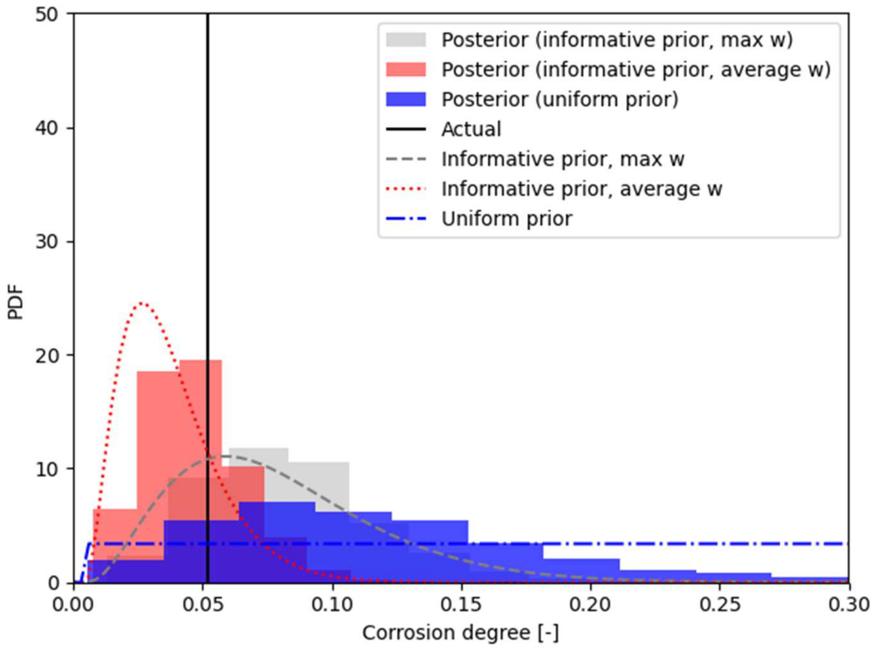


Figure 9: Posterior corrosion degree of a simply supported beam based on static strain measurements, with different assumptions on the prior distribution.

When combining the different sources of information, the weighing of the information and its significance is carried out within the Bayesian inference procedure. The more sensitive a measurement is to changes in the inferred parameter, the more the posterior distribution based on this measurement will shift towards the actual value. However, also the measurement and model errors will influence this shift. A more accurate measuring technique and more accurate model, accompanied by small errors, will lead to a narrower posterior distribution, better approximating the actual value. On the other hand, an increase in measurement and/or model error will lead to a vaguer posterior distribution. Within the Bayesian inference procedure, because updating is performed considering numerical model outputs, load and force redistributions are inherently accounted for. For example, when the corrosion degree of a reinforced concrete bridge is inferred based on measurements of displacements, within the Bayesian inference procedure, the model M should relate to a finite element model of the bridge under investigation, where effects of corrosion are accounted for, e.g., by adjusting the stiffness and the section of the reinforcement steel. This model then also accounts for the influence of changes in the corrosion degree on the force redistributions and hence on the corresponding deflections under a given load.

4.2. Updating of degradation models

The principle provided by Bayes' rule can also be applied in regression analysis. This methodology is well-described in literature in case of linear regression, e.g., in (Box & Tiao, 1973; Gamerman & Lopes, 2006; Gelman et al., 2004; Ghosh et al., 2006; Gregory, 2005; Lee, 2004). However, in most cases observational data is modelled by a function which is a nonlinear combination of the model parameters and depends on multiple variables. Available literature on this Bayesian nonlinear regression is rather limited (see, e.g., Gelman et al., 2004; Gregory, 2005). However, applying Bayesian updating of regression models is of particular interest in the assessment of existing concrete structures, as previously obtained information regarding regression parameters of degradation models can be updated towards posterior distributions of the regression parameters, taking into account experimental data of the degradation process or indirect information about the effect of the degradation with respect to strains, deflections, etc. The fact that prior information can be taken into account, moreover, enables to make sure that relevant regression models can be obtained even in case of very limited information, which provides a significant advantage compared to other statistical approaches.

Assume that the true value of the response variable $\tilde{y}$ can be predicted by a mathematical or numerical model $M(.)$ which is a non-linear function of R regression parameters β_i and depends on a vector $\boldsymbol{x}$ which represents an m-dimensional set of input parameters. If this model would be perfect and the true values $\tilde{\boldsymbol{x}}$ are exactly known, this model would predict the true response value $\tilde{y}$. However, due to the existence of uncertainties, the true value is given by:

$$\tilde{y} = y + \varepsilon = M(\boldsymbol{x}) + \varepsilon \tag{11}$$

where the error term ε is usually considered as a realization of a Gaussian random variable with mean 0 and standard deviation σ_ε, representing the measurement and model uncertainties. If N independent test results y_i are available for the response variable of N sets of corresponding input parameters $\boldsymbol{x}_i$, the likelihood of the experimental data can in general be written as:

$$L(y_1, \dots, y_N | \boldsymbol{x}_1, \dots, \boldsymbol{x}_N) = \prod_{i=1}^{N} \frac{1}{\sigma_\varepsilon} \phi\left(\frac{y_i - M(x_i)}{\sigma_\varepsilon}\right) \tag{12}$$

where $\phi(.)$ is the probability density function of the standard normal distribution. Based on the Bayesian principle, the prior information is given as the joint prior distribution $f'_B(\sigma_\varepsilon, \beta_1, \dots, \beta_R)$ regarding the standard deviation σ_ε of the error term and the regression parameters $(\beta_1, \dots, \beta_R)$. This prior distribution can be updated towards a posterior distribution, using the likelihood function, i.e.:

$$f''_B(\sigma_\varepsilon, \beta_1, \dots, \beta_R) = c \cdot f'_B(\sigma_\varepsilon, \beta_1, \dots, \beta_R) \cdot L(y_1, \dots, y_N | \boldsymbol{x}_1, \dots, \boldsymbol{x}_N) \tag{13}$$

where c is a normalizing constant.

When now considering again the situation with degradation models, a common discussion relates to fixing model parameters for the corrosion propagation phase in concrete. Rather than trying to fix these parameters in general for all cases, this Bayesian regression approach can be incorporated in the updating process when additional information becomes available. Consider for example the empirical model to predict the corrosion rate presented in (Vu & Stewart, 2000) and (Stewart & Suo, 2009):

$$M(\boldsymbol{x}) = i_{corr}(t_p) = i_{corr}(1) \cdot a \cdot t_p{}^b \tag{14}$$

$$i_{corr}(1) = \frac{d \cdot (1-WC)^e}{C} \tag{15}$$

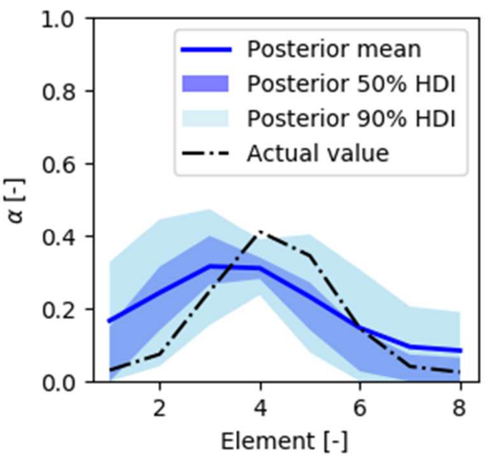
where t_p is the propagation time, $i_{corr}(1)$ is the corrosion rate at the start of corrosion propagation, WC is the water-cement ratio, C is the concrete cover, and a, b, d and e are regression parameters (with default values $a = 0.85$, $b = -0.3$, $d = 27$ and $e = -1.64$ according to (Stewart & Suo, 2009)). In case N measurements of the corrosion rate $i_{corr,j}$ and associated input vectors $\boldsymbol{x}_j = (WC, C, t_p)_j$ are available, the likelihood function (12) and posterior distribution (13) yield respectively:

$$L\left(i_{corr,1}, \dots, i_{corr,N} \middle| \boldsymbol{x}_1, \dots, \boldsymbol{x}_N\right) = \prod_{j=1}^{N} \frac{1}{\sigma_\varepsilon} \phi\left(\frac{i_{corr,j} - M(\boldsymbol{x}_j)}{\sigma_\varepsilon}\right) \tag{16}$$

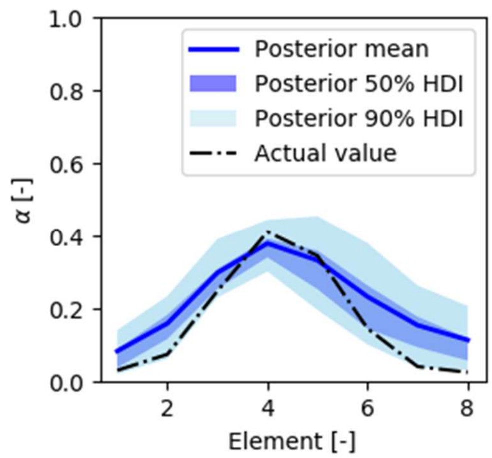
$$f_B''(\sigma_\varepsilon, a, b, d, e) = c \cdot f_B'(\sigma_\varepsilon, a, b, d, e) \cdot L\left(i_{corr,1}, \dots, i_{corr,N} \middle| \boldsymbol{x}_1, \dots, \boldsymbol{x}_N\right) \tag{17}$$

The likelihood and probability distributions can simply be added to the likelihood and distribution in relation to other variables and updated together. Prior information can moreover be based on literature data (such as mentioned for this specific case) or be based on vague prior information or information based on expert judgement.

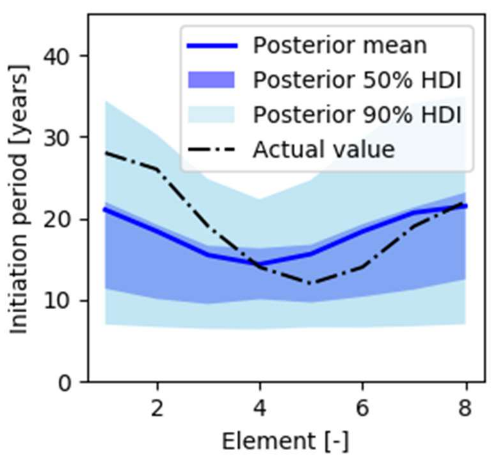
Finally, it is also important to notice that in case the corrosion rate is not measured directly, indirect measures may be used as for example corrosion degrees, deflections, crack widths, etc. to infer indirectly about the corrosion rates. In such case also the model uncertainties or model parameters can be taken into account in the likelihood function and the updating can be performed together with all other uncertainties. In doing so the power of Bayesian updating is fully exploited in a way that is not comparable to other statistical methods. An example of such an application can be found in (Vereecken, 2022) and is also illustrated in Figure 10. Here, a reinforced concrete beam with a length of 4 m, subdivided in eight elements along its length is considered. The distributions of the initiation period and corrosion rate are inferred based on heterogeneous measurement data, i.e., strain measurements at the fourth element of the beam under a static load combined with visual observations. From these results it is clear that not only the corrosion degree can be inferred, but that also the distributions of the initiation period and corrosion rate can be updated based on the measurement information.

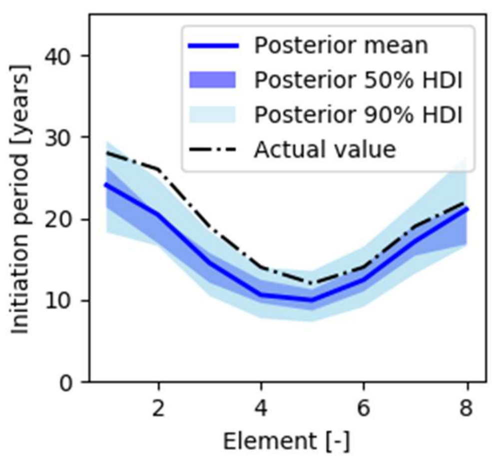


a) Posterior distribution of corrosion degree based on static strain data



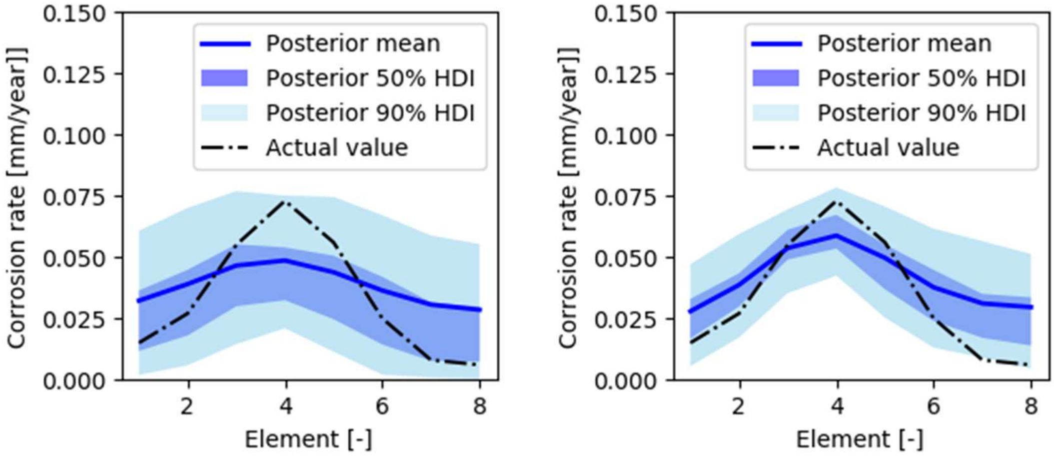
b) Posterior distribution of corrosion degree based on static strain data with visual observation of rust stains





c) Posterior distribution of initiation period based on static strain data

d) Posterior distribution of initiation period based on static strain data with visual observation of rust stains



e) Posterior distribution of corrosion rate based on static strain data

f) Posterior distribution of corrosion rate based on static strain data with visual observation of rust stains

Figure 10: Illustration on how Bayesian inference can be used in the updating of the variables in degradation models. Here, the initiation period and corrosion rate of a reinforced concrete beam are updated based on static strain data and visual observations.

4.3. Updating on the basis of information from quantitative quality control

The most important objective of quality control is to verify whether the delivered product or service complies with the specifications requested by the client. In general, quality control has a favourable effect due to the fact that the existence of quality requirements (such as conformity criteria) compels producers to deliver high quality products in order to avoid rejection by quality assessment. This effect has an influence on the probabilistic modelling of e.g., concrete properties of accepted concrete lots and also influences the structural reliability analysis of concrete structures. Bayesian approaches can be used to quantify this effect (Caspeele & Taerwe, 2013). For an assumed property (e.g., the concrete strength distribution) and for a given conformity criterion, one can calculate the probability that a concrete lot, characterized by a fraction defectives θ, is accepted. This probability is called the probability of acceptance and denoted as P_a. An example of such an operating characteristic curve is shown in Figure 11 in case of conformity criteria of type $\bar{x}_n \geq f_{ck} + \lambda\sigma$ for different values of the number of samples n and the parameter λ. Operating characteristics of compound conformity criteria as currently applied in EN206-1:2000 for concrete strength are given in Figure 12, considering also autocorrelation between consecutive test results.

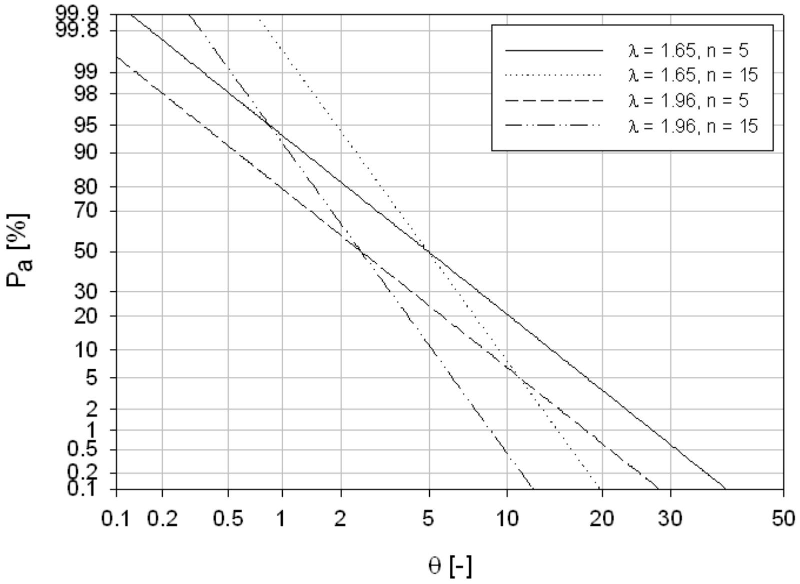
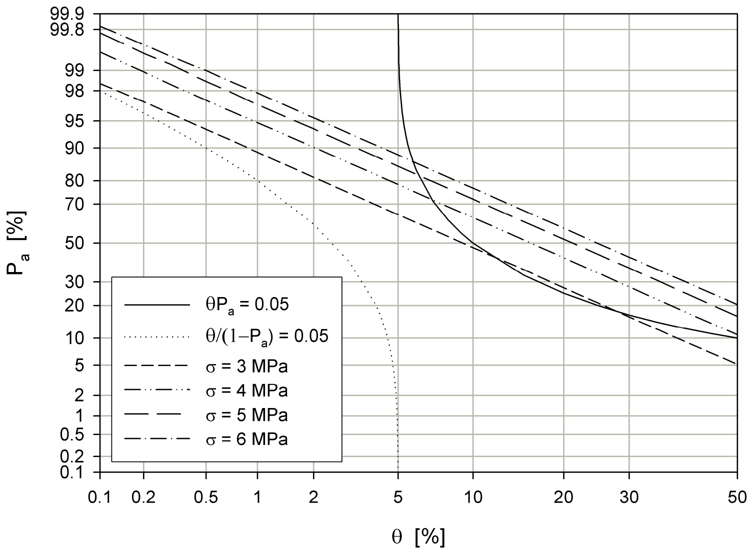
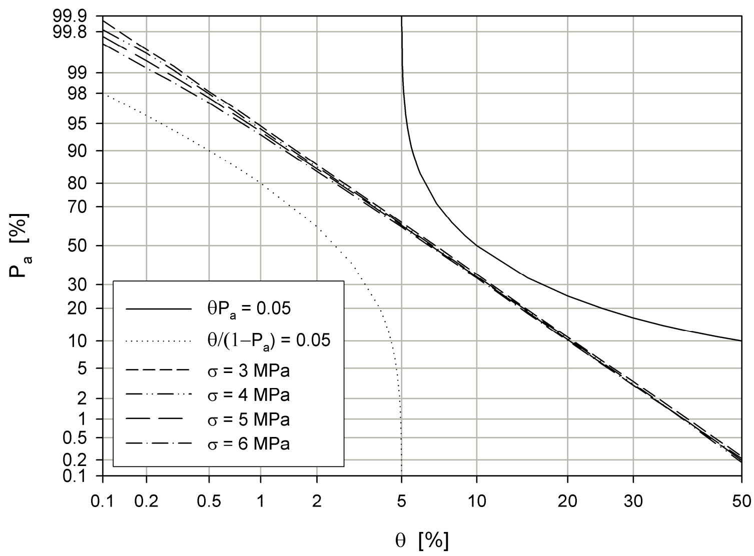


Figure 11: Operating characteristic curves corresponding to different conformity criteria of type $\bar{x}_n \geq f_{ck} + \lambda\sigma$ for different values of the number of samples n and the parameter λ



(a)



(b)

Figure 12: Operating characteristic curves corresponding to the compound conformity criterion for concrete strength in EN206-1 for initiation production (a) and continuous production (b), considering autocorrelated consecutive test results.

The filter effect of a conformity criterion is related to the probability of acceptance associated to the applied conformity control scheme. Due to the lower acceptance probability of a strength population with a high fraction defectives, the population of strength distributions shifts towards lower fractions defectives (which correspond to a higher quality with respect to e.g., concrete strength). Bayesian statistics provide the probabilistic framework for updating the (strength) distribution after conformity control, thus enabling to quantify the so-called filter effect, as follows:

$$f_{\Theta,o}(\theta) = \frac{P_a(\theta)\, f_{\Theta,i}(\theta)}{\int P_a(\theta)\, f_{\Theta,i}(\theta) d\theta} \tag{18}$$

with $f_{\Theta,i}(\theta)$ the prior distribution of the fraction defectives in incoming lots (designated 'i') and $f_{\Theta,o}(\theta)$ the posterior distribution of the fraction defectives in outgoing or accepted lots (designated 'o'). In case of structural reliability calculations, it is however more relevant to update the parameters of the strength distribution (i.e., the mean and standard deviation of e.g., the concrete strength).

In (Caspeele et al. 2014) a semi-analytical approach was developed to assess the filtering effect of complex conformity criteria accounting for autocorrelation between consecutive test results. Consider the following model for the concrete compressive strength *X*:

$$X = X_m + X_l \tag{19}$$

where X_m is a quantity describing the variation of the mean strength of different lots, i.e., X_m is normally distributed with mean μ_m and standard deviation σ_m, and X_l is a quantity describing the variation of the strength within a certain concrete lot, i.e., X_l is normally distributed with mean 0 and standard deviation σ_l. The mean and standard deviation of the offered (incoming) lots can be written as Equations (20) and (21) respectively:

$$\mu_i = \mu_m \tag{20}$$

$$\sigma_i = \sqrt{\sigma_m^2 + \sigma_l^2} \tag{21}$$

After conformity control, the posterior density function of X_m is given by:

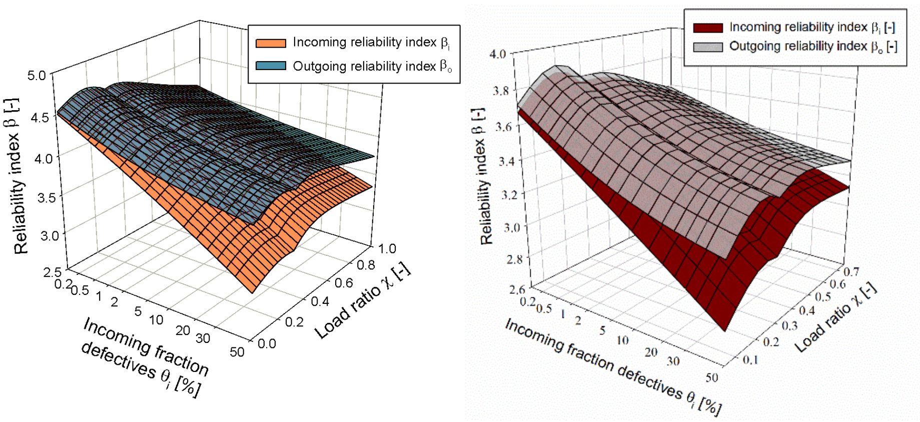
$$f_o(x_m) = \frac{\frac{1}{\sigma_m}\phi\left(\frac{x_m-\mu_m}{\sigma_m}\right)P_a(x_m|\ldots)}{\int_{-\infty}^{\infty}\frac{1}{\sigma_m}\phi\left(\frac{x_m-\mu_m}{\sigma_m}\right)P_a(x_m|\ldots)dx_m} \tag{22}$$

where $\phi(.)$ is the probability density function of the standard normal distribution and $P_a(x_m|\ldots)$ is the probability that a concrete lot with mean strength x_m is accepted by the conformity criteria. Further, the posterior predictive distribution of the concrete strength can then be calculated according to Equation (23) in case of the model outlined in Equations (19)-(22):

$$f_o(x) = \int_{-\infty}^{\infty} f(x|x_m, \sigma_l) \cdot f_o(x_m) dx_m = \int_{-\infty}^{\infty} \frac{1}{\sigma_l} \phi\left(\frac{x - x_m}{\sigma_l}\right) \cdot f_o(x_m) dx_m \quad (23)$$

where *f*(.) is the prior probability density function of *X*.

In (Caspeele et al., 2014) and (Caspeele, 2014), the influence of quality control of concrete on structural reliability has been assessed based on the procedure outlined above. It was shown that due to conformity control, a more uniform reliability is obtained in function of the incoming fraction defectives. Thus, conformity control reduces the dependency of the reliability index with respect to the parameter uncertainties of concrete strength distributions. In Figure 13(a), the filter effect is illustrated for the reliability of a concrete column subjected to compression. Similar results were obtained in (Botte et al., 2017) in case of conformity control of reinforcing steel considering the conformity criteria in EN 10080. The influence of the latter on the reliability of a concrete beam subjected to bending is shown in Figure 13(b). As can be observed in Figure 13, although most often quality control (or more specifically conformity control) is not taken into account directly in structural reliability calculations, it has a significant ability in filtering uncertainties of variables involved and considerably reduce the dependency of the structural reliability on the uncertainties related to the material properties, which is inherent to the production process of these materials.



(a) (b)

Figure 13: Influence of conformity control on the reliability index of a concrete (a) column subjected to compression (considering conformity control of concrete in accordance to EN206-1) and (b) beam subjected to bending (considering conformity control of steel in accordance to EN 10080): incoming and outgoing reliability indices β_i and β_o as a function of incoming fraction defectives θ_i and load ratio χ.

In (Vereecken and Caspeele, 2021), the conformity control of concrete durability parameters and its filtering effect on the design service life has been investigated. Durability parameters such as the diffusion coefficient have a direct influence on the service life of reinforced concrete structures. Applying conformity control to the diffusion coefficient leads to a lower mean value and standard deviation. When including these adjusted distributions for the diffusion coefficient in reliability analysis and analysis of the design service life, a positive effect is found, i.e., an increase in the service life of a batch of concrete subjected to this conformity control.

5. Outlook and future challenges

From the above overview of recent developments, it is clear that Bayesian updating techniques provide a unique tool for engineers to incorporate additional direct and indirect information about structures in all steps of the life-cycle assessment framework.

Nevertheless, several challenges remain to be tackled the coming decades in order to bring these new developments into practical applications and convey the *Bayesian way of thinking* into everyday engineering practice.

At the research level, more efforts need to be undertaken to develop easy-to-use engineering tools that enable to disguise the often complex numerical and probabilistic calculations and simulations that are involved. There is an urgent need for the development of commercial FEM software for structural analysis that enables to incorporate localized information about the structure such as measured concrete properties, monitoring data, durability parameters, etc. and automatically integrate this in a Bayesian calculation scheme enabling to make spatial predictions of the structural behaviour. Further, it is also necessary to orient research efforts to the quantification of suitable prior information in relation to measurement and model errors, as the current vague information that is available on this matter prevents more accurate posterior prediction of the structural behaviour. Especially in relation to degradation processes, research should step away from the intention of proposing generally applicable probabilistic models for the degradation process (which is very case specific) and orient towards updating degradation models along the lifetime of the structure.

At the level of practical applications, efforts should be oriented to develop a suitable assessment framework incorporating these Bayesian updating techniques. The optimization of investments in testing, monitoring and interventions is feasible with such techniques and should be more intensively exploited in order to come to cost-efficient, but adequate structural assessment and rehabilitation. There is an urgent need to step away from prescribing an extensive testing program without looking at the Value of Information (VoI) this data provides for the structural analysis to be performed. Frequently, investments in testing and monitoring can be more adequately spent if the VoI is properly considered, i.e., by quantifying the influence of the additional information on the posterior uncertainties and the associated decision making through a pre-posterior analysis (see e.g., Vereecken et al., 2021). Finally, in order to exploit the updating feasibilities during the lifetime, efforts and investments during the exploitation of the structures should be oriented to more frequent material testing rather than only making point-wise investigations and assessments in time. In this way, the Bayesian updating of the life-cycle performance becomes more effective and a more accurate estimation of the end of lifetime can be obtained.

6. Conclusions

Bayesian updating techniques have proven to be of undeniable importance when requiring to incorporate different sources of information into the assessment process of concrete structures. Although the last decennia significant progress has been made to analytically and numerically simulate the degradation process of concrete structures and their associated structural performance prediction in time, dealing with the large uncertainties involved requires the use of updating techniques that enable to incorporate direct and indirect information from inspection, testing and monitoring when these become available. Moreover, the combined integration of this information into the performance prediction proves to enable much more accurate predictions compared to the situation when this data is analysed separately. Also, the need to step away from classical ad-hoc testing approaches and the formulation of testing and measurement campaigns without considering the Value of Information is stressed. Further, it was also identified that several challenges still remain in relation to the development of such Bayesian updating methodologies, not least the quantification of suitable prior information as well as the values of model and measurement uncertainties to be considered. The integration of these approaches into the practical assessment process is however proven to be feasible and more research efforts coming years should be oriented towards integrating such approaches further in commercial FEM software in order to provide a more accessible and easy-to-use platform enabling to introduce the *Bayesian way of thinking* in all steps of the life-cycle assessment process of concrete structures.

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8. Disclosure statement

No potential competing interest was reported by the authors.

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