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Risk evaluation on concrete strength assessment with NDT technique and conditional coring approach

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Abstract:
In-situ concrete strength assessment is commonly based on the implementation of Non-Destructive Tests (NDT) and coring of several specimens for Destructive Tests (DT). The most widely used non-destructive (ND) techniques are rebound hammer and ultrasonic pulse velocity. From the resulting data of NDT and compressive strength test results on specimens, a conversion law is identified which can then be used to estimate the compressive strength at any location in the structure. Since this process is very sensitive to many uncertainty sources, recent RILEM recommendations have revised the assessment paradigm by considering it in a probabilistic framework. The challenge is no longer to estimate the true concrete strength, but to limit the risk of a wrong estimation within a certain admissible interval. In this context, it is shown how synthetic simulations are used to capture the main features of this problem and are a firm basis for justifying the relationship between the most influencing parameters and the quality of the assessment. In addition, the effect of conditional coring, which consists in the selection of coring positions on the basis of previous NDT results, is highlighted and quantified. Finally, the methodology that makes possible to define the required number of cores for a given target accuracy is presented.

Keywords
concrete strength, concrete variability, cores, in-situ assessment, measurement precision, non-destructive tests, rebound hammer, risk, ultrasonic pulse velocity

1 Introduction

Current practice for assessing the in-situ concrete strength usually combines measurements obtained from non-destructive techniques (the most widely used being the rebound hammer and the ultrasonic pulse velocity techniques) and results from destructive tests (DT) performed on several cores extracted from the structure under assessment. In order to identify a “conversion model” between the non-destructive and destructive test results, several approaches have been proposed in the past: regression-based approaches [1-3], calibration-based approaches [4-7], and the bi-objective approach [8-9]. Once a conversion model is identified, it can be used to estimate local strength values by converting new ND test results performed at different test locations within the structure. Further analysis can provide additional information, such as a probabilistic distribution of the strength, or its mean and variability.

However, many sources of uncertainty influence the variability of these estimates such as: in-situ concrete variability (intrinsic variability) [10], sampling uncertainty [11], measurement uncertainty [12], and model uncertainty (i.e. model shape and influence of uncontrolled factors) [13-14]. Therefore, controlling the quality of the assessment (i.e. how close the estimated strength is to the true strength) is a real challenge for engineers assessing the in-situ strength of concrete, and many studies have addressed this issue. In this context, an important aspect that also needs to be addressed is what is understood by "true strength". This may appear as a philosophical issue since there are many factors that influence the strength that is measured on samples that are taken from a given structure [15]. Therefore, it is considered herein as being a "reference strength" corresponding to the value obtained from cores that are extracted and tested according to relevant standards. Regarding the influence of the testing techniques, some researchers [7, 16-17] are, for example, pessimistic about the use of the rebound hammer and consider it is unable to provide a reliable estimate of concrete strength. On the contrary, other researchers like Malhotra [18] consider that the accuracy of compression strength estimates obtained from test specimens cast, cured, and tested under laboratory conditions using a properly calibrated hammer lies between ±15 and ±20%, although it can increase up to ±25% for the concrete strength in a structure [18]. Other results from Szilágyi and Borosnyói [19] indicate that the expected error of the strength estimate obtained using a Schmidt rebound hammer under general service circumstances is about ±30% while FHWA [20] states that the accuracy of the rebound hammer to estimate the in-situ compressive strength is between ±30% and ±40%. Regarding the ultrasonic pulse velocity technique, when using a conversion model established/calibrated for the case under consideration, concrete strength can be estimated with a ±20% accuracy [21-22]. Furthermore, an extended collaborative research project [23] has shown that the accuracy of the final strength estimates depends on three parameters: the range of variation of strength in the structure, the repeatability of the ND test results and the sensitivity of strength to the ND parameter. These issues justify the efforts devoted to quantify the repeatability of test results for rebound [24] and ultrasonic pulse velocity [25], as well as to analyse the sensitivity of strength to test results [26]. Nevertheless, other studies [6, 27-28] have reported that combining test results from rebound hammer and ultrasonic pulse velocity can improve the quality of the strength assessment. Despite these different research initiatives, their results show that there is no consensus between specialists regarding the quality of concrete strength assessment using ND test results. Still, the uncertainty on the final strength estimate can be addressed using statistical methods, as indicated in the ACI 228.1R standard [29], or using common statistical validation tests to derive confidence factors [30]. However, estimating the effective quality of the assessment accounting for all the relevant factors remains an open issue that requires further improvements and methodologies providing more in-depth knowledge. For example, it is noted that many of the available studies are based on experimental programmes developed in laboratory environments that do not reproduce the full complexity of the real problem.

The main difficulty comes from the random character of the uncertainty sources and from the impossibility of analysing them directly in the field, due to cost restrictions and the limited size of any assessment programme. Although the post-processing of data from real case-studies can provide relevant information [31-32], a synthetic approach was recently proposed

[8, 33-34] to overcome some of these limitations. This synthetic approach involves simulating both the structure under assessment and the assessment programme itself, including the test results processing stage. This approach was recently used in an international benchmark challenge to compare the efficiency of different assessment programmes [4], and to analyse and quantify the role of the most influencing factors [35]. These analyses were performed to determine how the uncertainty (or the quality of the assessment) is influenced by the number of test locations for the extraction of cores NC, the precision of test results (within-test variability), the quantity to be assessed (i.e. a mean value, a variability, etc.), and the approach for identifying the conversion model [36]. In current practice, the common way to select the locations for extracting cores within the NDT locations is independent of the ND test results. However, studies like [4, 35, 37] indicate that locations to extract cores should depend on the prior ND test results, following a procedure called "conditional coring". This approach was also considered in [36] and seen as a factor that can affect the quality of the strength assessment.

In light of this discussion, the objective of the current article is to go further into this issue and quantify how the uncertainty of the strength assessment depends on the main input factors. It is first shown that uncertainty must be at the core of the assessment process, by assessing the uncertainty of the test results, of the parameters of the conversion model and of the final estimates of concrete properties. In order to do so, risk curves will be introduced as a way to quantify the probability of a wrong assessment of compressive strength, for a given concrete and a given set of investigation conditions. These curves can be established using synthetic simulations and their analysis will enable the identification of the most influencing factors of the final quality of the assessment. Therefore, it will be possible to identify what must be the minimum number of cores in order to limit the referred risk at a prescribed level.

Section 2 defines the probabilistic framework of the revised paradigm for on-site NDT strength assessment and introduces the concept of risk curves. The programme of synthetic simulations that delivered a broad range of data is presented in Section 3. These data are then analysed in Section 4 to illustrate the role of the most influencing factors for concrete strength assessment. Finally, the data are processed in Section 5 to derive operational conclusions in terms of the assessment means to reach a prescribed target.

2 Revising the NDT strength assessment paradigm

2.1 The need to consider uncertainty

The conversion model is the mathematical expression used to transform the ND test results into an estimated strength. It is well-known that this model is not an exact one and that it is influenced by several uncertainty sources which are described herein. Figure 1a reproduces what is commonly done by practitioners, when a given conversion model, which can be either a pre-existing one or a specific model adapted to the structure and concrete under assessment, is used. The final output of this process is the estimated concrete strength. When the problem is analysed in more detail, it appears that Fig. 1a over-simplifies the process and it becomes clear that uncertainties must be considered, as described in Fig.1b.

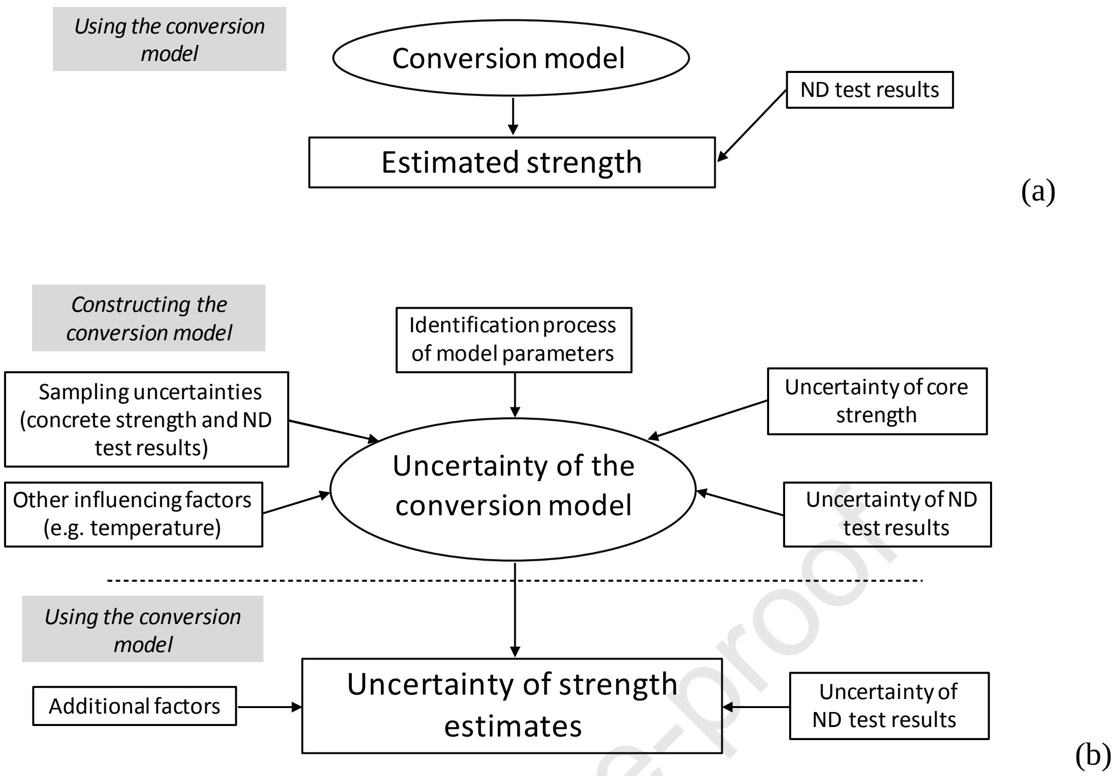


Figure 1 (a) Usual concrete strength estimation process; (b) Uncertainties arising in the different stages of the concrete strength estimation process.

The flowchart of Fig. 1b is divided into two stages that correspond, respectively, to the model identification and to the model use, and shows that uncertainty (or errors) can impact the process in several stages. In the first main stage (that of the conversion model identification), the following factors are seen to have an influence:

- statistical (sampling) uncertainty, due to the limited size of the dataset that is used to identify the model, i.e. typically governed by the number of cores that are extracted,
- test result uncertainty, on core strength test results as well as on ND test results, which depends mostly on the technique itself, but also on the device, on the expertise of who takes the measurement and on the environmental context. For the case of core test results, this also includes all biases that can appear during the extraction of the core and its preparation for the compression test,
- factors related to the identification process itself (from the data to the model parameters), such as the choice of the mathematical shape of the model, or the method that is used to select the location of the cores. This set contains a large number of degrees of freedom and has a large potential for improvement,
- additional uncontrolled factors not considered in the analysis but that can have some influence on the core strength, on the NDT result, or on their relationship (e.g. temperature or carbonation).

As a consequence of the combined effect of these factors, the conversion model that is identified in a particular case is partially the result of chance, since a different model (i.e. a different set of model parameters) would have been identified if the same process was repeated. This is the main explanation of the trade-off between the many models that are available in the literature and that were analysed in detail in [34]. When the second global stage of the flowchart is considered, the “uncertain” conversion model is used with new data (i.e. new NDT results) and with the influence of possibly different or additional uncontrolled factors. It must be clear that the final output, i.e. the estimated concrete strength, is the result of a random process and cannot be considered as a deterministic value.

2.2 A risk-based approach for estimating mean concrete strength and local strength values

To consider the uncertainties in concrete strength assessment implies a deep revision of the framework that has been followed by practitioners until now. The classical paradigm is deterministic, and its challenge is the identification of the "reference value" of concrete strength. The revised paradigm, which considers uncertainties and risk, explicitly considers that concrete strength is a random variable whose best estimate can be defined using the following tolerance interval:

$$\left(f_{c,ref} - \Delta f_{c,ref}\right) < f_{c,est} < \left(f_{c,ref} + \Delta f_{c,ref}\right) \qquad \text{(Eq. 1)}$$

where $f_{c,ref}$ is the reference value (unknown) of concrete strength, $f_{c,est}$ is the estimated concrete strength and $\Delta f_{c,ref}$ is half of the tolerance interval around the reference strength. One can note that Equation 1 can be modified if the tolerance interval is defined in relative terms (i.e. percentages) instead of absolute ones. Equation 1 can be written similarly for the mean strength of concrete over the investigation domain (i.e. by replacing $f_{c,ref}$ by $f_{c,\mathrm{mean},ref}$ and $f_{c,est}$ by $f_{c,\mathrm{mean},est}$) and for local strength values (i.e. by replacing $f_{c,ref}$ by $f_{c,i,ref}$ and $f_{c,est}$ by $f_{c,i,est}$).

If the assessment process is repeated multiple times (which is impossible in real situations due to the costs, but easy by using the synthetic approach previously referred), it is possible to derive the statistical distribution of the estimates $f_{c,est}$ of the strength parameter under analysis. The cumulative distribution function (CDF) curves presented in Figs. 2a-2b illustrate the statistical scatter that can be obtained for different situations of the estimated strength values. The scatter in the CDF curves is due to the effect of all sources of uncertainty described in Figure 1b.

As written in Equation 1, the acceptable distance between the reference strength $f_{c,ref}$ and the estimated strength $f_{c,est}$ is $\Delta f_{c,ref}$, which can also be written as:

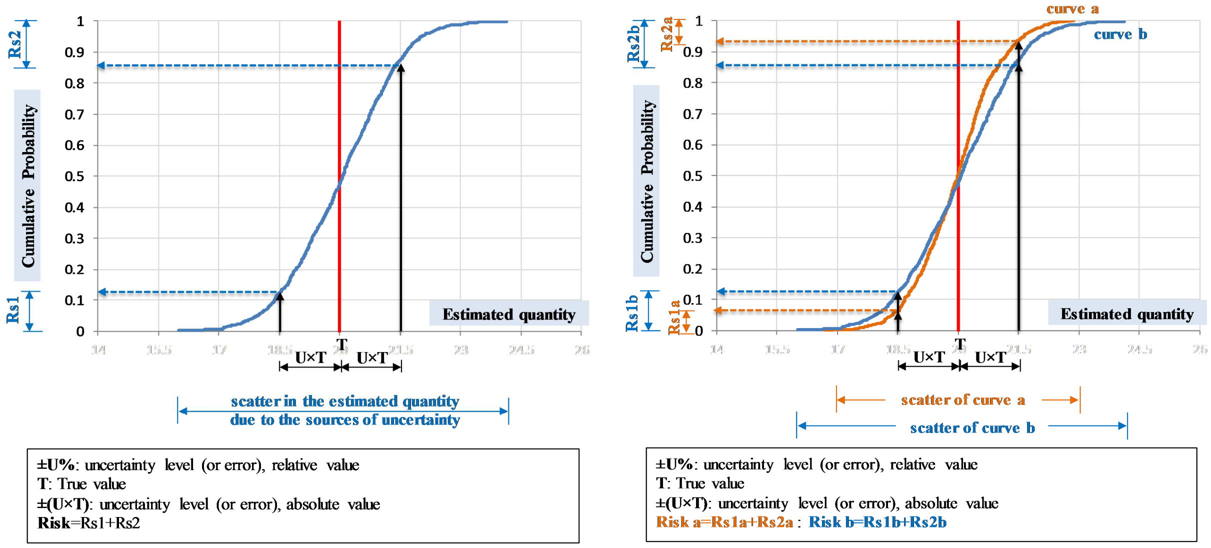
$$\Delta f_{c,ref} = U \times f_{c,ref} \qquad \text{(Eq. 2)}$$

where U represents half of the relative tolerance interval defined as a percentage of $f_{c,ref}$.

The target is reached if the estimated strength falls within the tolerance interval. As shown in Fig. 2a, there is some probability that the estimated strength falls outside the target tolerance interval (here +/- U% of the reference strength). This probability is defined by the sum of two probabilities which correspond, respectively, to an excessive underestimation (Risk 1) and an excessive overestimation (Risk 2). The total risk of a wrong estimation is therefore:

$$\alpha = \text{Risk 1} + \text{Risk 2} \qquad \text{(Eq. 3)}$$

Reversely, (1 - α) denotes the confidence level of estimation, i.e. the probability that the estimated value falls within the prescribed tolerance interval. When compared to the traditional assessment approach, the main change of this proposal is that both the uncertainty of the assessment process and the resulting risk are considered. According to this revised paradigm, the challenge is no longer to identify the reference strength but to estimate it to be within a tolerance interval, and at a given or accepted risk.



(a) (b)

Figure 2. Proposed concept to derive a risk value corresponding to a specific uncertainty level using CDF curves: (a) illustration of the proposed concept; (b) changes in the risk value due to changes in the scatter of the CDF curve.

The risk value can also be seen to depend on the target tolerance interval since the risk of being wrong decreases as the tolerance interval widens. Figure 2b illustrates how a change in the scatter of the CDF curve also changes the risk value. Curve b corresponds to a more scattered distribution and its larger uncertainty may be the result, for instance, of using a lower number of cores for the conversion model identification stage. As a consequence, the risk of a wrong estimation increases.

Determining the concrete mean strength is usually not the only objective of the assessment. The assessor is often interested in deriving local strength values from the NDT results at certain locations. As for the mean of concrete strength, the estimated local strength departs from the reference value of the local strength. It is possible to compute the mean error of this estimation, for instance using the root mean square error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{NC}\left(f_{c,i,tef} - f_{c,i,iest}\right)^2 / NC} \quad \text{(Eq. 4)}$$

where NC is the number of cores for which $f_{c,i,ref}$ and $f_{c,i,est}$ can be compared. RMSE has the same units as the strength and, as an estimate of local error, should be as small as possible. Its practical interest lies in the fact that it provides a more direct measure of the magnitude of the error associated to the estimated strengths. Unlike the distribution of the estimated mean strength, the RMSE value is always positive. The unacceptable situation occurs when the RMSE value exceeds a prescribed target value, which can be expressed either in absolute terms (i.e. in MPa) or in relative terms, e.g. as a given percentage U' of the standard deviation of the strength $s(f_c)$. The larger the target RMSE value, the lower the risk that it will be exceeded. To establish an expression similar to those of Equations 1-2, this exceedance probability k can be determined by:

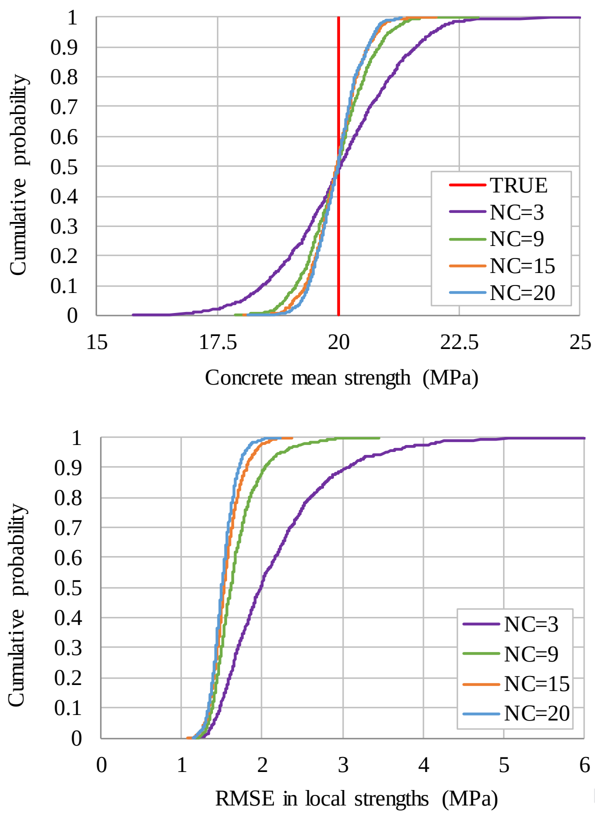
$$P(\mathrm{RMSE} \quad = \mathrm{U}' \times \ \mathrm{s}(f_c) \ > \mathrm{RMSE}_{1-\mathrm{k}}) = k \qquad \text{(Eq. 5)}$$

where k denotes the risk value (i.e. the probability of having a RMSE value larger than the admissible value) and $\mathrm{RMSE}_{1\text{-}k}$ represents the admissible value of RMSE defined by the $(1\text{-}k)^{th}$ percentile of the distribution of RMSE values obtained by repeating the assessment process multiple times using the synthetic approach.

As can be seen, when estimating mean strength and local strength values, the risk of a wrong assessment (i.e. of being outside a prescribed tolerance interval) can be determined from the corresponding CDF curves. Section 2.3 will examine the importance of the CDF curves in more detail and will show that this risk is governed by the number of cores NC. Section 3 will then explain how the CDF curves can be built by processing simulation results. Risk curves will finally be drawn and analysed in Section 5.

2.3 Risk curves

CDF curves can be used to show the simulation results. As an example illustrating the results obtained for the estimation of the mean strength and for the local RMSE values, Figure 3 show curves where simulated distributions are plotted for four NC values (respectively 3, 9, 15 and 20 cores) and for a specific concrete with a reference mean strength of 20 MPa and a reference standard deviation of 3 MPa. These simulations were performed by considering high precision ND test results, i.e. involving a low value of test result uncertainty. Full details about the simulation process are provided in Section 3.

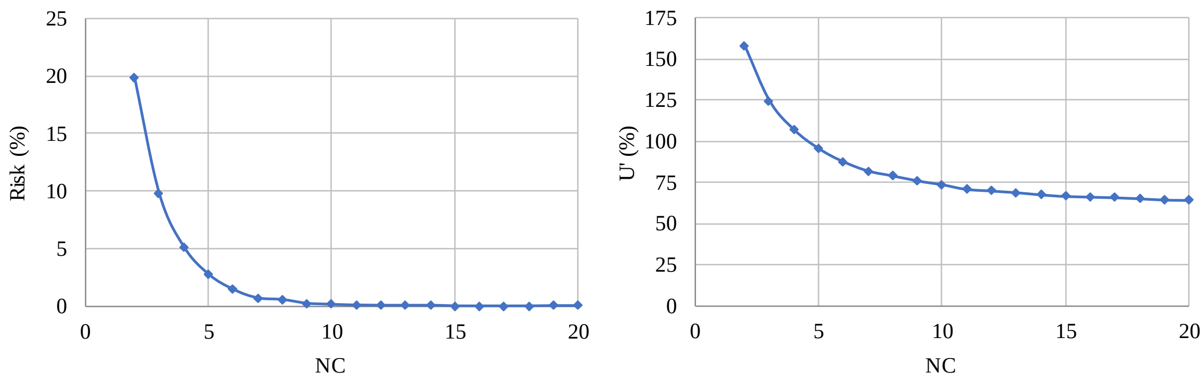


(a) (b)

Figure 3. Cumulative distribution of results for a varying number of cores: (a) estimated mean strength; (b) local error, RMSE values for local strength estimates.

Figures 3a and 3b exhibit a very different pattern. For the mean strength estimates, the S-shaped cumulative distribution is close to symmetric and slowly converges towards the reference mean strength as NC increases. When considering a given value of U, for example +/- 10%, which in this case is +/- 2MPa, the corresponding risk value can be seen to decrease as NC increases. Regarding the distribution of the RMSE of local strengths, the CDF curves can be seen to be asymmetric, since there is a minimum value of the RMSE as a result of having the various sources of uncertainty represented in Fig. 1b, including the error about the shape of the conversion model.

Risk curves represent, for any criterion, how the risk value varies with the number of cores. Figure 4a shows the risk curve obtained after numerically simulating multiple assessment scenarios with increasing values of NC, considering a +/- 10% tolerance interval on mean strength of the studied concrete and high precision ND test results. According to this example, the risk can be seen to get to a value below 5% as soon as NC reaches 5 cores. For the RMSE assessment, instead of evaluating the risk curve, a value of the risk k was set (see Eq. (5)), which corresponds to a high percentile of the RMSE distribution (e.g. k = 5%, which is equivalent to saying that the RMSE value is larger than this percentile in one case out of twenty). For that risk, the value of U' was then determined from the value of $RMSE_{1-k}$ obtained from the distribution of RMSE values. The results obtained after numerically simulating multiple assessment scenarios with increasing values of NC are illustrated in Fig. 4b. This figure shows that the curve converges towards a horizontal asymptote that, for the simulated concrete and considering a standard deviation of 3 MPa, is about 60%, i.e. 1.8 MPa. Therefore, this means that, even with a very large number of cores, there is a 5 % risk that the error on local strength is larger than 1.8 MPa, which corresponds to 60% of the standard deviation of the concrete strength. The outputs of synthetic simulations can be post-processed with the same steps whatever the concrete properties and the precision of ND test results that are considered. Although risk curves and curves of the U' values will generally follow the same patterns, each specific case (i.e. concrete + test results) will have its own curves. Furthermore, it is noted that even though the risk for RMSE values is always discussed herein using curves of the U' values, for the sake of simplicity, risk curves and curves of the U' values are both termed risk curves from this point on.



(a) (b)

Figure 4. Risk curve for the assessment of the mean value of the concrete strength (a) and curve of the U' values corresponding to a 5%-risk for local error ($RMSE_{95}$, see Eq. (5)) (b).

3 Research methodology and dataset generation

3.1 Research aims: optimal number of cores and advantages of conditional coring

As can be seen from the curves presented in Fig. 4, increasing the number of cores reduces the risk of an incorrect assessment. However, (a) the rate of reduction depends on the objective (i.e. the parameter under assessment such as the mean strength or a local strength), (b) since the risk curves converge towards a certain limit, there is a little interest in increasing excessively the number of cores without obtaining a significant improvement. Consequently, the objective of the research presented herein is to better understand how the various influencing parameters control the assessment errors, in order to provide guidelines regarding the "optimal" number of cores that should be considered. This optimality concept involves a trade-off between the cost of sampling and the accuracy/risk associated with the assessed values. As referred before, the assessment paradigm needs to be revised to consider the risk involved in the assessment of a given quantity. Risk curves are the tools that make it possible to quantify the number of cores that is required to estimate a quantity (e.g. mean strength) with an acceptable accuracy level.

The first goal of this study is to quantify the required number of cores that will enable to determine the assessment parameters (i.e. the mean value of concrete strength and local values of concrete strength) within a prescribed tolerance interval and with an acceptable risk. The second goal of the study is to check the real efficiency of conditional coring when compared to predefined coring, i.e. when cores are taken at predefined locations instead of locations selected after a careful analysis of the distribution of ND test results. As this way of defining the location of cores does not consider the ND test results, it will be named random coring (RC) hereon. In order to achieve this second goal, risk curves are developed for each assessment parameter considering both random coring (RC) and conditional coring (CC).

3.2 Framework for the synthetic simulations and considered assumptions

The idea of synthetic simulations was proposed in [4, 35] as being a very efficient process to better understand the NDT investigation approach. The process involves developing a synthetic environment (Fig. 5) that reproduces as closely as possible the main features found in a real investigation process, namely:

(a) the physical properties of the materials, such as strength, carbonation or moisture content, whose statistical distribution is either fitted to real datasets or simulated using theoretical distributions;
(b) the NDT properties and their measurement process, considering that NDT properties depend on the values of governing factors such as strength f_c and moisture content H;
(c) the implementation of the NDT investigation approach, which includes the measurement stage (and the simulation of the measurement uncertainty), the data processing and the model identification stage.

In this synthetic environment, a set of functions calibrated based on knowledge drawn from literature reviews express how the NDT properties depend on strength and other influential factors. In the strength assessment process, M is the conversion model identified from measurements that describes how strength depends on the properties measured by the NDT.

The main advantage of synthetic simulations is twofold. First, the quality of a strength assessment can be assessed by comparing the reference value of strength (which is known), and the estimated value determined by the expert (who does not know the corresponding reference value). The second advantage is that simulations can be repeated several times, e.g. through a Monte Carlo process, to obtain multiple realizations of a certain result that can then be statistically post-processed. By doing so, the conclusions that are obtained are seen to be more robust than those drawn from a single case-study, even a real one. For further details on the synthetic simulation process, the reader is referred to [8, 9]. Reference is also made to specific applications where synthetic simulation was instrumental, namely [34] where the trade-off issue between the conversion model parameters during the model identification stage is analysed, [35] where the investigation strategies of several expert investigators are reproduced, and [39] where the most important variables governing the final accuracy of the assessed strength are identified.

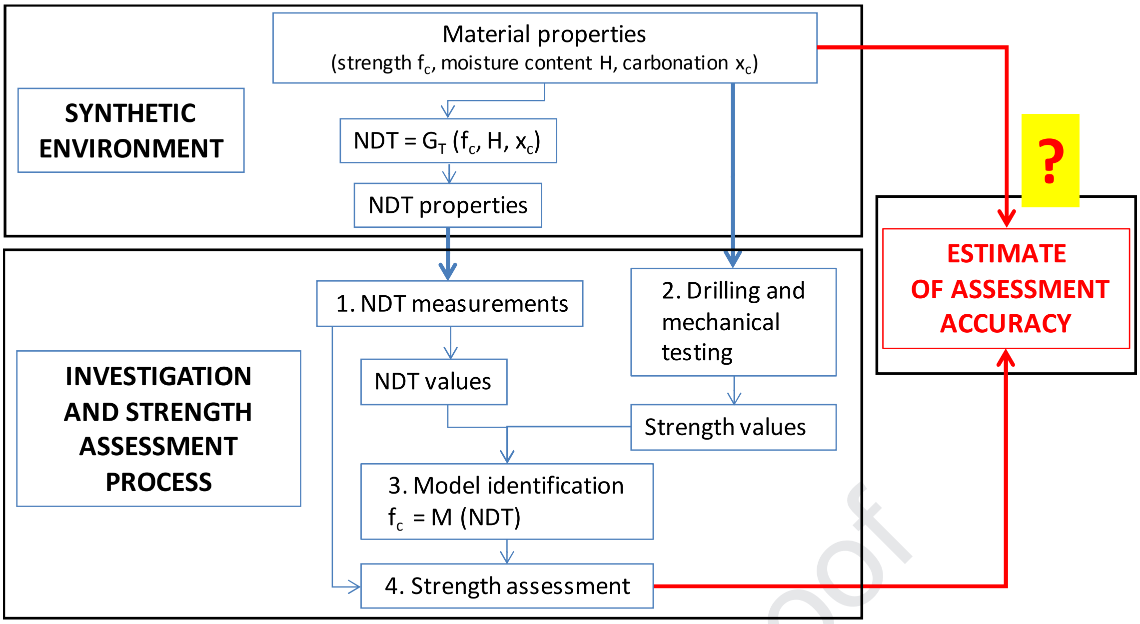


Figure 5. Illustration of the use of synthetic simulations for strength assessment

According to Fig. 6, the simulation process defines a given concrete with properties specified by statistical distributions and their parameters, and different types of investigations (that include varying the number of cores and the way to select them). The same investigation and assessment process are then repeated NI times (NI = number of Monte-Carlo repetitions). For each repetition, all measurements (NDT and DT results) are simulated and a variety of conversion models can be fitted, from which sets of strength estimates are derived. From these results, additional parameters are calculated (mean strength $\bar{f}_{c\ est\ i}$, $RMSE_i$). After finalizing the repetitions, further post-processing of the results allows extracting more synthetic information such as the statistical properties of the outputs and the risk curves as shown in [36]. Furthermore, it provides a simple framework to compare the outcomes of several options often considered in engineering practice [35, 38]. As an example, the flowchart of Fig. 6 shows that there is an external loop on the number of cores NC that enables to consider multiple options regarding the number of cores to analyse the true effect of this variable on the parameters being assessed.

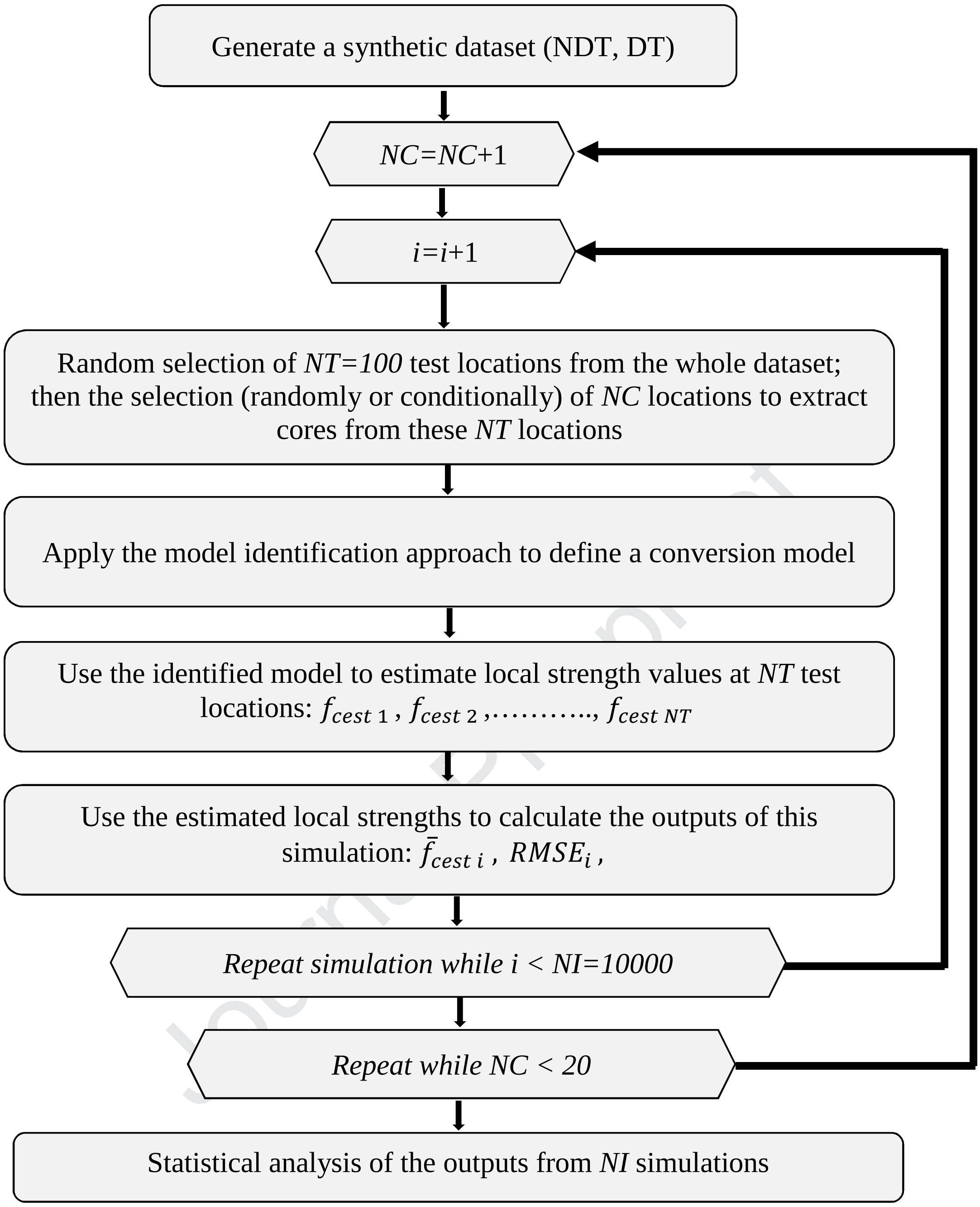


Figure 6. Flowchart of the simulator used in this study

In the present study, focus is given to the development of risk curves as a tool for rational decision-making and on analysing the influence of conditional coring. The first results on this issue were obtained in [36] where conditional coring was used based on a pre-screening with rebound hammer tests. This study improves previous research by increasing the number of Monte-Carlo iterations (NI) (10000 instead of 1000 in order to get more stable results) and by considering a wider range of concrete strength properties (Table 1).

Datasets symbols	$f_{c,\mathrm{mean}}$	$s(f_c)$ (MPa)	$CV(f_c)$ (%)

			(MPa)		
D10-10-HP	D10-10-MP	D10-10-PP	10	1	10
D10-15-HP	D10-15-MP	D10-15-PP	10	1.5	15
D10-20-HP	D10-20-MP	D10-20-PP	10	2	20
D10-25-HP	D10-25-MP	D10-25-PP	10	2.5	25
D10-30-HP	D10-30-MP	D10-30-PP	10	3	30
D20-10-HP	D20-10-MP	D20-10-PP	20	2	10
D20-15-HP	D20-15-MP	D20-15-PP	20	3	15
D20-20-HP	D20-20-MP	D20-20-PP	20	4	20
D20-25-HP	D20-25-MP	D20-25-PP	20	5	25
D20-30-HP	D20-30-MP	D20-30-PP	20	6	30
D30-10-HP	D30-10-MP	D30-10-PP	30	3	10
D30-15-HP	**D30-15-MP**	**D30-15-PP**	**30**	**4.5**	**15**
D30-20-HP	D30-20-MP	D30-20-PP	30	6	20
D30-25-HP	D30-25-MP	D30-25-PP	30	7.5	25
D30-30-HP	D30-30-MP	D30-30-PP	30	9	30
D40-10-HP	D40-10-MP	D40-10-PP	40	4	10
D40-15-HP	D40-15-MP	D40-15-PP	40	6	15
D40-20-HP	D40-20-MP	D40-20-PP	40	8	20
D40-25-HP	D40-25-MP	D40-25-PP	40	10	25
D40-30-HP	D40-30-MP	D40-30-PP	40	12	30
D50-10-HP	D50-10-MP	D50-10-PP	50	5	10
D50-15-HP	D50-15-MP	D50-15-PP	50	7.5	15
D50-20-HP	D50-20-MP	D50-20-PP	50	10	20
D50-25-HP	D50-25-MP	D50-25-PP	50	12.5	25
D50-30-HP	D50-30-MP	D50-30-PP	50	15	30

Table 1. Characteristics of the 75 synthetic datasets considered in the present study, where $f_{c,\text{mean}}$, $s(f_c)$ and $CV(f_c)$ stand for the mean value, the standard deviation and the coefficient of variation of the selected concrete strength distributions. Bold characters refer to the specific concrete case for which detailed results are provided in the following.

The quantities that were assessed are the local strengths and the mean strength, and the conversion model is identified using the least-squares regression approach considering a linear model. The NDT data are based on ultrasonic pulse velocity test results, and involve three options regarding the precision of test results, which are simulated by considering three levels of the within-test-repeatability (WTR) error. The WTR values are 50 m/s, 100 m/s and 200 m/s and are assumed to correspond to high precision (HP), medium precision (MP) and poor precision (PP) test results, respectively. These values were chosen to be representative of what can be found in practice, from the analysis of several on-site investigations [33, 39]. Some measurement errors are also involved in the destructive tests (i.e. the core strength test results), which are much less documented in the literature since these tests cannot be repeated on the same specimens. Regarding the precision (within test repeatability) of core strength test results, it is defined with thresholds of 1 MPa, 1.5 MPa and 2 MPa for HP, MP and PP respectively. The assumption taken for all simulations is that the precision level of destructive tests is identical to that of NDT (as an example, this means that when NDT are PP, DT are also PP). Since conditional coring is identified as a possible efficient way of taking cores, its performance is systematically compared with that of random coring.

In order to derive more general conclusions than in previous studies [9, 36], the variety of concrete distributions has been extended and 75 synthetic datasets are considered in the present work. These datasets cover a wide range of concrete mean strengths (from 10 MPa to 50 MPa) and concrete strength variabilities (with coefficients of variation ranging from 10%

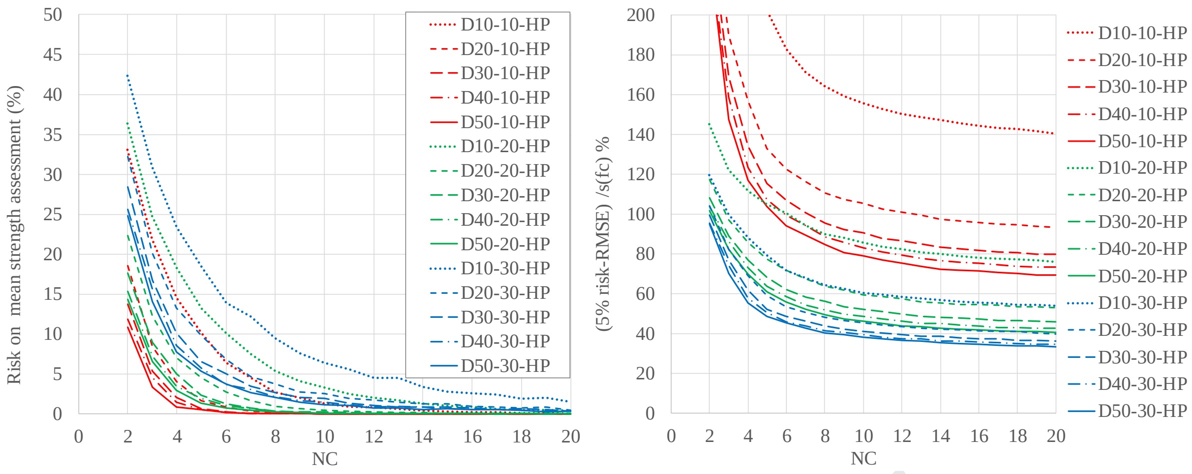
to 30%). Each synthetic dataset is denoted by the letter "D" followed by the population mean strength, $f_{c,\mathrm{mean}}$, then the population concrete strength variability (in terms of coefficient of variation, $CV(f_c)$, and the abbreviation of the test result precision represented by HP (High Precision), MP (Medium Precision) or PP (Poor Precision). The characteristics of these datasets are given in Table 1. Each dataset is defined by a sample of 100 values sampled from a normal distribution with the parameters given by the corresponding concrete properties. The 100 values represent the reference concrete strength $f_{c,i,ref}$ at 100 possible test locations (NT) for which the reference ultrasonic pulse velocity test results $V_{i,ref}$ are then also simulated using the synthetic mode presented in [35].

4 Results of the simulation study

4.1 Effect of the most influencing parameters when considering random coring

All figures in the following (Figs. 7-11) are risk curves computed for the assessment of the mean strength, with a tolerance interval of +/- 10%, and the 5%-risk RMSE local error ($RMSE_{95}$), as previously plotted in Fig. 4. Each figure presents the results obtained for 15 concretes involving five mean strength values and three different levels of strength variability. Different line types are used to distinguish the various mean values and three colours are used to represent the different variability values (red curves for $CV(f_c)$ = 10%, green curves for $CV(f_c)$ = 20% and blue curves for $CV(f_c)$ = 30%). For the sake of clarity, results corresponding to other intermediate values of $CV(f_c)$ (i.e. 15% and 25%) are not presented.

Previous studies [9, 36] have shown that the accuracy of concrete strength assessment is mostly influenced by the number of cores that are considered (thus justifying the concept of risk curves), the precision of the test results (assessed through WTR), and the concrete characteristics (mean and variability). These findings are confirmed herein. Regarding the assessment of concrete mean strength, all risk values decrease when NC increases, as expected, and a statistical stabilization of the conversion model is observed for larger sample sets (Fig. 7a). The risk value quickly becomes negligible (i.e. lower than 5%) in most cases as NC is more than 8 or 10. An exception to this general result is found for the D10-30-HP concrete that has simultaneously a low strength and a large variability. For this concrete, as discussed in the Introduction (see Fig. 2b), the in-situ concrete variability $s(f_c)$ is a source of uncertainty and leads to a more scattered CDF curve. Since the interval $\pm U \times T$, with $T = f_{c,\mathrm{mean}}$, is the same for datasets having the same $f_{c,\mathrm{mean}}$, a larger scatter in the CDF curve leads to higher risk values.



(a) (b)

Figure 7. Risk curves for 15 concretes, considering high precision (HP) test results and random core selection, for the assessment of the mean strength (a) and of the local error U' on $RMSE_{95}$ (b).

Regarding the assessment of local strength values, the 15 curves of Fig. 7b show interesting patterns with two main characteristics:

- increasing NC is still seen to decrease the relative uncertainty of the strength estimate for a 5% risk level. However, for more than 10 to 12 cores, the reduction in the relative uncertainty becomes marginal,
- all curves exhibit a convergence but the asymptotic uncertainty is not equal to zero. This means that, even for a very large number of cores, it is impossible to estimate local strength values very accurately. To be more explicit, a horizontal asymptote at U' = 40% means that $RMSE_{95} = 0.4 \times s(f_c)$, or that there is a 5% risk that the local error is larger than 40% of the concrete standard deviation.

Figure 8 also shows that all red curves stand above the other curves, which means that larger errors are expected for concretes with a low variability. This result is a spurious effect deriving from the definition of the error, which is taken as a relative error in Equation 4. In practice, this result means that the local error has the same magnitude or exceeds the concrete standard deviation (asymptotes stand at about 100%), but this standard deviation is low. If an alternative definition of the error had been selected (i.e. an absolute error, in MPa), the curves would have been different. This issue may become a key factor since the target error may be expressed either in relative or absolute terms. This must be kept in mind when processing the results, in order to avoid spurious conclusions. Finally, it is noted that the relevance of the concrete strength distribution on the accuracy of the assessment is also confirmed, since lower mean strengths and higher variability concretes correspond to the curves having a higher risk (Fig. 7a). This can be easily understood since a reduced range in the variation of strength (i.e. a case with the same coefficient of variation but a lower mean strength) reduces the quality of the regression between core strength results and ND test results at the conversion model identification stage.

4.2 Effect of the precision of test results

The effect of the precision of test results is known to be very significant [9, 36] and clearly underestimated in real practice. Figure 8 shows the risk curves with medium precision (Fig. 8a) and poor precision (Fig. 8b) for the assessment of mean strength, with a tolerance interval of +/- 10% and using the same formatting conventions that are used in Fig. 7 with high precision test results.

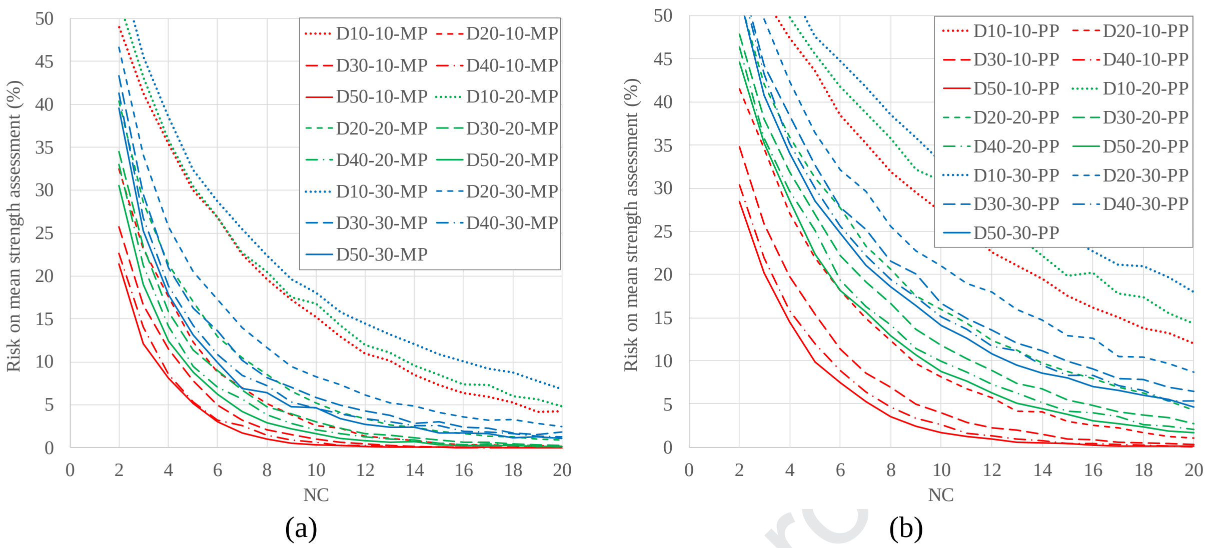


Figure 8. Risk curves for 15 concretes, for the assessment of mean strength with random core selection: (a) with medium precision (MP) test results, (b) with poor precision (PP) test results.

All comments related to the results presented in Fig. 7 are applicable to those of Fig. 8. Still, these results exhibit a slower convergence towards zero risk as a consequence of the larger test result uncertainties. In most cases, 8 or 10 cores are enough to get a risk below 5% risk when considering HP test results (Fig. 7a), and this number increases to 12 to 14 cores when MP test results are involved (Fig. 8a). However, all curves for the low strength concrete ($f_{c,\mathrm{mean}}$ = 10 MPa) stand above the others and show a very slow convergence, which means that more cores are needed to get a low risk: for instance, between 14 and 17 cores are required with MP test results for a 10% risk. For such a concrete, the +/- 10% tolerance interval corresponds to a +/- 1 MPa range around the reference strength, which is very difficult to capture and requires more than 20 cores to reduce the risk to a value below 5 %. The situation for the risk curves with PP test results (Fig. 8b) is even worse since, with NC = 20, the risk value is less than 5% for only 50% of all curves. In the overall, these results show that any recommendation regarding the number of cores required to assess the concrete strength with a given level of reliability needs to explicitly consider the precision of the ND test results.

4.3 Efficiency of conditional coring in improving the quality of assessment

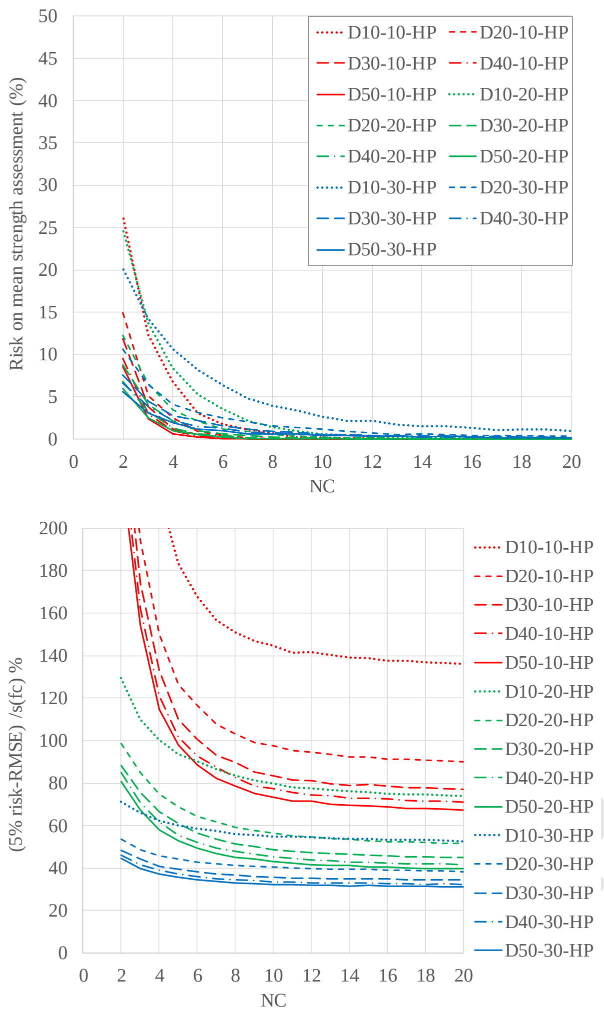
Reasons to favour the use of conditional coring were already discussed before (e.g. see the Introduction). Results providing further quantitative arguments are now presented based on series of Monte-Carlo simulations that were carried out by considering simultaneously the two coring options, i.e. random coring and conditional coring. The method used by the algorithm for selecting the core location is as follows: (a) rank all NDT results from the lowest to the highest value, (b) subdivide the set into NC subsets, (c) select a test location where the NDT result value is closest to the median value of each subset. Except for the way of core selection, all other features are kept the same in the analyses with the conditional selection (i.e. NT = 100 for ND test results, regression using a linear model, NI = 10000, and

NC varying from 2 to 20). The final resulting CDF curves were used to construct the risk curves corresponding to the cases involving conditional coring.

Figures 9 and 10 use the same formatting convention of Figs. 7 and 8. The results of Figs. 7 and 8 were obtained with random coring whereas those of Figs. 9 and 10 were obtained with conditional coring. This means that, in all simulations reproducing conditional coring, a series of ND test results were carried out first (as shown in the flowchart of Fig. 6) and the locations to extract cores were determined after processing the NDT results, in order to cover the whole range of measured values. By ensuring a better coverage of the concrete strength variability, this extra stage aims at reducing the uncertainty of the conversion model. The efficiency of conditional coring in reaching this objective is expected to be significant, especially when the number of cores is small and when the NDT results are more accurate (i.e. for HP or MP test results).

A direct comparison of the curves obtained with random coring and conditional coring provides useful information:

- Regarding the assessment of the concrete mean strength (Figs. 7a and 9a), the curves that consider conditional coring exhibit a lower level of risk for a given value of NC. As expected, since conditional coring improves the coverage of the strength distribution, the assessment is more efficient, especially when a small number of cores is involved.
- Regarding the error on local strength assessment with HP non-destructive test results (Figs. 7b and 9b), the advantages of conditional coring are less obvious. The magnitude of the asymptotes is unchanged, and the effect on the relative uncertainty for local strength assessment (green and blue curves) is only seen when a small number of cores is considered (conditional coring leads to a faster convergence for NC $\leq$ 6 or 7). However, conditional coring is ineffective for concretes with a small variability (red curves). In this case, the differences between the measured values are mostly due to measurement errors instead of resulting from true variations in the material properties. Moreover, the conversion model is not significantly improved due to the low range of variation of concrete strength.
- The comparison between Figs. 8a and 10 provides additional information regarding the effect of combining conditional coring with MP test results. This comparison indicates that the efficiency of conditional coring reduces as the precision of the test result changes from HP to MP.



(a) (b)

Figure 9. Risk curves for 15 concretes, considering high precision (HP) test results and conditional coring, for mean strength assessment (a) and local error U' on $RMSE_{95}$ (b).

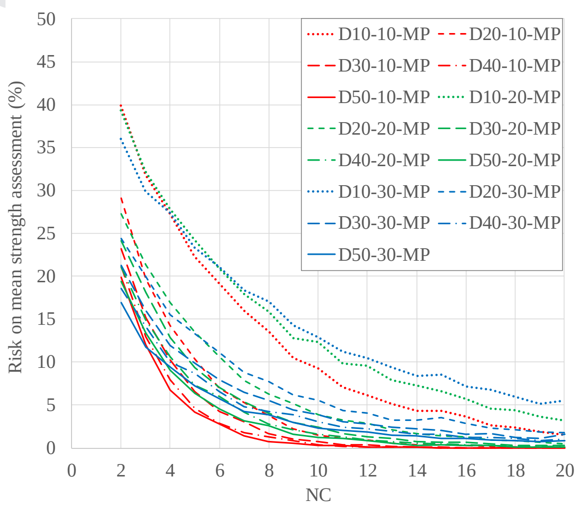


Figure 10. Risk curves for 15 concretes, considering medium precision (MP) test results and conditional coring, for the assessment of the mean strength.

5 Prescribing a minimum number of cores compatible with a target assessment accuracy

5.1 *Effect of the precision of test results*

The important influence of the NDT result precision was shown in the previous sections and can be further analysed by comparing the risk curves for the assessment of both the mean strength and the errors on local strength. This comparison is highlighted in Fig. 11 that shows results only for one specific concrete (considering random coring RC and conditional coring CC; as well as the three options of ND test results precision). For the sake clarity, the curves focus on concrete D30-15, which is seen as an "average concrete" in terms of mean strength and strength variability within the set of 25 combinations that were considered in the numerical simulations.

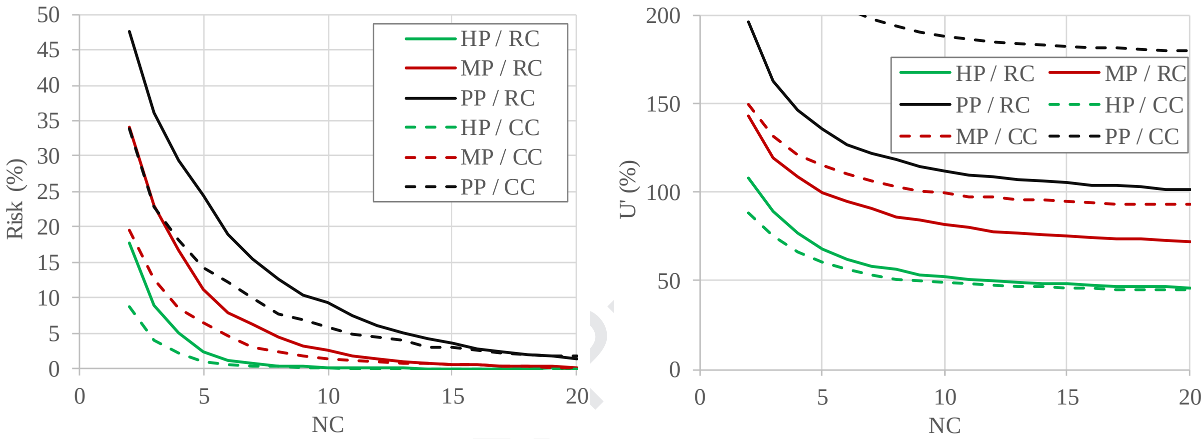


Figure 11. Comparison of risk curves for concrete D30-15, considering random coring (RC) and conditional coring (CC) and the three levels of test results precision: risk for the assessment of the mean strength (a) and of the local error U' on $RMSE_{95}$ (b).

The significant effect of the ND test results precision is visible in both plots of Fig. 11 since the black curves (poor precision (PP) test results curves) are always largely above the brown curves (medium precision (MP) test results curves) and the green curves (high precision (HP) test results curves). Regarding the assessment of the mean strength, the required NC to have a risk lower than 5% when considering random coring is 5, 8 and 14 cores for NDTs with HP, MP and PP test result precision, respectively. These critical values drop to 3, 6 and 11, respectively, for the same conditions but involving conditional coring. Therefore, it can be seen that, whatever the measurements precision, conditional coring saves two cores to achieve the same quality of the assessment of mean strength.

The effect of the measurements precision on the local error U' (local strength assessment) is somewhat different. As can be seen, when HP test results are involved, conditional coring improves the assessment and, for a given level of error, slightly reduces the number of cores that would be required with random coring. However, this statement does not hold for MP and PP test results. In these cases, using conditional coring actually leads to an increase of the local error U' on $RMSE_{95}$, as shown by the brown and black curves of Fig. 11 b). This can be explained by the fact that the measurement error, while having no effect on the average conversion model (that would correspond to a 50% risk for $RMSE_{95}$), may have a negative effect in few cases (and these would induce the worst cases, corresponding to the 5% risk $RMSE_{95}$).

5.2 What is the required number of cores?

Previous sections discussed and provided arguments for the fact that, in order to adequately consider the uncertainties involved in on-site concrete strength assessment, a new paradigm is required, so that any assessment considers a target tolerance interval and the risk of a wrong assessment. In practice, this means that the analyst must first select a target tolerance (e.g. +/- 10% for the mean strength) and an acceptable risk (e.g. 5% for the mean strength and local strength). Once these values are fixed, the results of previous sections show that there is a direct relation between these values and the required number of cores. Simultaneously, this implies that a minimum number of cores can be established as a function of these values.

In real practice, the number of cores should be as small as possible, due to several factors (e.g. to reduce costs, to reduce the damage to the construction, etc.). ACI 214.4R [40] provides an expression to determine NC (with 95% confidence) for a specific concrete strength variability and an admissible predetermined error between the estimated mean strength and the reference population mean (assuming the reference population of concrete strength follows a normal distribution). However, the applicability of this expression is restricted to the assessment of the mean strength and provides large values of NC because it is derived by assuming that the assessment is solely based on DT results. Other requirements on this issue can be found in the European standard EN 13791 [5] that sets the minimum number of cores for regression analysis at 18 (e.g. see Alternative 1 as termed in this standard). Alternatively, ACI 228.1R [29] requires a minimum of six to nine test locations to extract cores, enforcing that two cores should be extracted from each location, which amounts to a total of 12 to 18 cores. These standards do not consider the specificity of the concrete under assessment (e.g. its variability) and do not provide any information about the error that might be involved in the estimated strength value.

<u>Looking at mean strength only</u>

From the analysis of the quality of the assessment performed in the present study, it can be seen that the minimum value of NC depends on many influencing factors: in-situ concrete variability, precision of test results, the prescribed error (or the uncertainty level), the way that the locations to extract cores are selected, the quantity to be assessed (mean strength, standard deviation or local strength) and the confidence level in the estimated value. Therefore, the results of the numerical simulations of the present study were post-processed in order to derive values for the required minimum number of cores to reach a prescribed target in a variety of situations.

Tables 2 and 3 summarize some of the outcomes of this analysis, namely by providing the number of cores required to estimate the mean strength with a +/- 10% confidence interval and a 5% risk (i.e. with a 95% confidence level), for HP and MP test results, respectively. The two tables consider a large range of concrete properties (in terms of mean strength and coefficient of variation) and provide results for random coring and conditional coring. The ">" sign indicates cases where more than 20 cores are needed to reach the prescribed target.

Tables 2 and 3 show identical trends: there is an increase of the required number of cores when the mean concrete strength decreases and the concrete variability increases, the former factor being the most influential of the two. This result is expected, since estimating the concrete mean strength with a +/- 10% tolerance interval is easier if the mean strength is larger and the variability lower. It can also be seen from the results that most values of the required number of cores are lower (sometimes much lower) than the values prescribed by EN 13791:2013 (i.e. NC = 18) [5]. The only case where this value is exceeded is when the mean strength is 10 MPa and MP test results are considered. In this situation, the tolerance interval is only +/- 1MPa, which is a very ambitious absolute value. Therefore, the prescribed number of cores according to EN 13791 appears to be too conservative for HP and MP NDT results.

The results also show that conditional coring is beneficial in most cases, thus generally requiring a lower number of cores to be extracted. For example, Table 2 shows that, thanks to conditional coring, 7 cores are enough to reach the target for any concrete (i.e. any combination of mean strength and variability). The efficiency of CC is reduced with MP test results but 11 cores are enough when the mean strength is 20 MPa or more.

$f_{c,\,mean}$ (MPa)	CV(f_c) (%)									
	10		15		20		25		30	
	RC	CC	RC	CC	RC	CC	RC	CC	RC	CC
10	7	5	8	6	9	6	10	7	12	7
20	4	4	5	4	5	4	6	4	7	4
30	4	3	4	3	5	3	5	3	7	3
40	3	3	4	3	4	3	5	3	6	3
50	3	3	4	3	4	3	4	3	6	3

Table 2. Required number of cores for the assessment of the mean strength for various concrete characteristics and high precision (HP) test results according to the type of core sampling approach (/random coring (RC) *vs* conditional coring (CC)).

$f_{c,\,mean}$ (MPa)	CV(f_c) (%)									
	10		15		20		25		30	
	RC	CC	RC	CC	RC	CC	RC	CC	RC	CC
10	19	14	19	16	20	17	>	19	>	>
20	9	8	10	9	11	10	11	10	14	11
30	6	6	7	7	8	8	10	8	11	9
40	6	5	7	6	8	7	8	7	10	7
50	6	5	6	6	7	6	8	6	9	7

Table 3. Required number of cores for the assessment of the mean strength for various concrete characteristics and medium precision (MP) test results according to the type of core sampling approach (random coring (RC) *vs* conditional coring (CC)).

<u>Looking at the local error on strength estimation</u>

For the case where the local error on strength estimation is considered, the value of the required NC depends on how the error is defined as a function of RMSE. Equation 5 considers U' = RMSE/s(f_c), which defines the local error as a fraction of the standard deviation of the concrete strength. Alternatively, the local error can be defined as a fraction of the concrete mean strength (i.e. U" = RMSE/$f_{c,\ mean}$) or as an absolute parameter (i.e. U"' = RMSE, in MPa). These two possibilities lead to the following alternative expressions with the same confidence level (1 – k):

$$P\left(\mathrm{U}'' \times f_{c,\mathrm{mean}} > \mathrm{RMSE}_{1-\mathrm{k}}\right) = k \qquad \text{(Eq. 6)}$$

$$P(\mathrm{U}''' > \mathrm{RMSE}_{1-\mathrm{k}}) = k \qquad \text{(Eq. 7)}$$

where Equation 6 expresses the local error using U" in %, and Equation 7 uses the absolute value U"', in MPa. When considering scenarios where both the mean strength and the standard deviation of strength can change, these different expressions (Equations 5-7) do not lead to equivalent requirements, as illustrated in Table 4. The first line of Table 4 corresponds to the concrete D30-20, for which the three expressions provide the same thresholds T:

Eq. 5 $f_{c,\mathrm{mean}}$ = 30 MPa; $CV(f_c)$ = 20%; $s(f_c)$ = 6 MPa; U' = 50%; T = 3 MPa
Eq. 6 $f_{c,\mathrm{mean}}$ = 30 MPa; U" = 10%; T = 3 MPa
Eq. 7 U"' = 3 MPa; T = 3 MPa

However, for other scenarios, these expressions lead to different thresholds, depending on the characteristics of the selected concrete. For each of the concrete scenarios considered in Table 4, the bold number defines the most severe threshold. As discussed before based on risk curves, the value of NC that is required depends directly on the requirement threshold. As a consequence, since this threshold depends both on the criterion and on the concrete characteristics (mean strength and variability), a minimum value of NC can only be derived once the criterion is specified.

Concrete denomination	$f_{c,\mathrm{mean}}$ (MPa)	$CV(f_c)$ (%)	$s(f_c)$ (MPa)	Eq. 5 (MPa)	Eq. 6 (MPa)	Eq. 7 (MPa)
D30-20	30	20	6	**3**	**3**	**3**
D10-10	10	10	1	**0.5**	1	3
D10-30	10	30	3	1.5	**1**	3
D50-10	50	10	5	**2.5**	5	3
D50-30	50	30	15	7.5	5	**3**

Table 4. Magnitude of the requirement on local error, for different concrete strengths and for three possible expressions defining these requirements (U' = 50%, U" = 10%, U"' = 3 MPa).

Table 5 provides values of NC for the RMSE_{95} (i.e. the local error corresponding to a 5% risk) for all the combinations of concrete considered in the present study and HP test results. The NC value presented for each concrete corresponds to the less severe value (i.e. the lowest one) from those resulting from Equation 6 (with U" = 10%) and Equation 7 (with U"' = 3 MPa). Furthermore, this value is set to a minimum of 3 in cases where the strict application of the criteria leads to a smaller value. As in Tables 2 and 3, the values of NC are compared for the RC and CC approaches. The general trend of the results presented in these tables is less clear to analyse because they are obtained from the combination of two criteria that have opposite effects: Equation 6 governs the results for low strength and high variability concretes, while equation 7 governs the results for high strength and high variability concretes. Still, the two expressions lead to the same results for the D30-20 concrete which is at the centre of the table. Even though 20 cores are not enough to assess the local strength within the prescribed tolerance interval in some cases (e.g. for concretes with $f_{c,\text{mean}}$ larger than 40 MPa and $CV(f_c)$ lower than 15%), the target tolerance is reached in most situations with a low number of cores. The effect of conditional coring is still beneficial in some cases and can save several cores (between 1 and 4). Of course, these results change when the precision of the test results also changes.

$f_{c,\text{mean}}$ (MPa)	$CV(f_c)$ (%)									
	10		15		20		25		30	
	RC	CC	RC	CC	RC	CC	RC	CC	RC	CC
10	3	3	3	3	3	3	3	3	3	3
20	5	5	5	5	6	4	6	4	8	3
30	8	7	10	8	12	10	7	5	7	3
40	17	12	>	>	9	7	6	4	6	3
50	>	>	>	>	8	6	6	3	5	3

Table 5. Required number of cores to comply with the local error target for various concrete characteristics and high precision (HP) test results according to the type of core sampling approach (random coring (RC) *vs* conditional coring (CC)).

6 Conclusions

A large programme of synthetic simulations covering an extended range of concretes was performed to determine the number of cores needed for assessing the in-situ compressive strength of concrete. Even though having more cores is known to reduce the uncertainty in the identified conversion model and, therefore, on the concrete strength assessment process itself (in terms of mean strength or local values of strength), the proposed study suggests the need for a paradigm shift in the concrete assessment process. The results highlight the importance of considering a target tolerance interval and an accepted risk (or confidence level) when performing the assessment. For cases where the uncertainty on local strength estimates is also necessary, the study shows that different ways of expressing this tolerance interval will lead to significantly different results.
The precision of test results is a crucial parameter in the assessment process. The knowledge of the NDT result precision (i.e. the WTR) is a critical point that should be addressed in any in-situ investigation. Since the final uncertainty of all strength estimates depends significantly on this precision, it should be quantified for each specific situation. Furthermore, it was shown that a better precision of the ND test results enables to significantly reduce the number of cores required to estimate the concrete properties.

Prescribing a unique value for the minimum number of cores, that is expected to cover all situations and lead to reliable concrete strength properties, is however meaningless. The optimal number of cores depends on many factors such as the concrete characteristics (i.e. the mean strength and the strength variability). The precision of ND test results, that can be easily estimated through the WTR, also has a major influence. Risk curves were developed to quantify how, in most cases, increasing the number of cores reduces the risk of a wrong estimation, i.e. of being outside the target tolerance interval.

The advantage of considering conditional coring was confirmed in most cases, especially when HP non-destructive test results are involved. Regarding the assessment of the mean strength, 2 or 3 cores can be saved by using CC instead of randomly taking cores.

The post-processing of the simulation results enabled the identification of the minimum number of cores that are required, in each specific context, to reach a given target. This number is, in many cases, significantly lower than the one recommended by the EN 13791 standard, paving the way towards a more common use of NDT techniques. The two targets (i.e. mean strength, local strength) were analysed separately but their results can easily be combined in a given in-situ investigation if the assessor wants to assess at the same time mean strength and local strength with a given confidence interval. However, since performing such statistical analyses each time an engineer wants to assess a structure is impossible, simple rules (or tables) need to be derived. Such rules are easier to apply and do not require specific references to the background. This challenge was recently undertaken by the RILEM TC 249-ISC, and practical results were published RILEM guidelines [38].

These results also lead to the identification of open issues that will deserve further investigation:

- recent research results have shown that NDT investigation opens the way towards the assessment of concrete variability, which is a key issue in structural assessment [8, 41]. Such an additional target would require a similar approach, as it is considered in the RILEM TC 249-ISC recommendations.
- In synthetic simulations, the same type of precision level was assumed for destructive tests (i.e. core strength test results) and NDT results. It is however difficult in practice to estimate the effective precision of core strength test results. This issue will deserve further attention, and the contribution of ND test results on cores before compression tests will have to be investigated.
- The major influence of NDT results precision has been ignored in most of past scientific studies. It is probably the reason why there is no consensus about the added-value of combining several NDT techniques for a more reliable assessment of concrete strength (many studies have shown that the combination improves the assessment while many others have reached an opposite conclusion). This issue needs to be clarified by re-analysing all existing data in the light of new knowledge, which will be a relevant way to finally reach a reliable conclusion.

Compliance with Ethical Standards

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Conflict of Interest: The authors declare that they have no conflict of interest.

References

[1] Montgomery DC, Runger GC. Applied statistics and probability for engineers, 5th Ed. John Wiley & Sons; 2010.

[2] DeCoursey W. Statistics and probability for engineering applications. Elsevier; 2003.

[3] Walpole RE, Myers RH, Myers SL, Ye K. Probability & statistics for engineers & scientists, 9th Ed. Pearson Prentice Hall; 2012.

[4] Breysse D, Balayssac JP, Biondi S, Borosnyói A, Candigliota E, Chiauzzi L, Garnier V, Grantham M, Gunes O, Luprano V, Masi A., Pfister V, Sbartaï ZM, Szilágyi K. Non destructive assessment of in situ concrete strength: comparison of approaches through an international benchmark. Materials and Structures. 2017 50(2):133.

[5] EN 13791. Assessment of in-situ compressive strength in structures and precast concrete component. European Committee for Standardization, Brussels: 2013.

[6] Kheder GF. A two stage procedure for assessment of in situ concrete strength using combined non-destructive testing. Materials and Structures. 1999 32(6):410-417.

[7] Pucinotti R. Reinforced concrete structure: Non destructive in situ strength assessment of concrete. Construction and Building Materials. 2015 75:331-341.

[8] Alwash M, Sbartaï ZM, Breysse D. Non-destructive assessment of both mean strength and variability of concrete: a new bi-objective approach. Construction and Building Materials. 2016 113:880-889.

[9] Alwash, M. Assessment of concrete strength in existing structures using nondestructive tests and cores: analysis of current methodology and recommendations for more reliable assessment. PhD thesis, University of Bordeaux: 2017.

[10] Szilágyi K, Borosnyói A, Zsigovics I. Extensive statistical analysis of the variability of concrete rebound hardness based on a large database of 60 years experience. Construction and Building Materials. 2014 53:333-347.

[11] Pereira N, Romão X. Assessment of the concrete strength in existing buildings using a finite population approach. Construction and Building Materials. 2016 110:106-116.

[12] JCGM 100. Evaluation of measurement data - Guide to the expression of uncertainty in measurement. Joint Committee for Guides in Metrology, Geneva: JCGM 2008.

[13] Der Kiureghian A, Ditlevsen O. Aleatory or epistemic? Does it matter?. Structural safety. 2009 31(2):105-112.

[14] Breysse D, Balayssac JP. Strength assessment in reinforced concrete structures: from research to improved practices. Construction and Building Materials. 2018 182:1-9.

[15] Spalvier A, Bittner JA, Hall K, Popovics JS. Comparison of Core and In-Place Compressive Strengths for Early-Age Concrete. ACI Materials Journal. 2019 116(3):63-72.

[16] Carino N. Nondestructive test methods. In: Nawy EG (ed.). Concrete construction engineering handbook, 2nd Ed. CRC press; 2008.

[17] Brencich A, Cassini G, Pera D, Riotto G. Calibration and reliability of the rebound (Schmidt) hammer test. Civil Engineering and Architecture. 2013 1(3):66-78.

[18] Malhotra V. Surface hardness methods. In: Malhotra VM, Carino NJ (eds.). Handbook on nondestructive testing of concrete, 2nd Ed. CRC press; 2004.

[19] Szilágyi K, Borosnyói A. 50 years of experience with the Schmidt rebound hammer. Concrete Structures. 2009 10:46-56.

[20] FHWA. Guide to non destructive testing of concrete. US Department of Transportation, Federal Highway Administration, Washington DC: 1997.

[21] Komlos K, Popovics S, Nürnbergerová T, Babal B, Popovics JS. Ultrasonic pulse velocity test of concrete properties as specified in various standards. Cement and Concrete Composites. 1996 18(5):357-64.

[22] Popovics S, Rose JL, Popovics JS. The behaviour of ultrasonic pulses in concrete. Cement and Concrete Research. 1990 20(2):259-70.

[23] Balayssac JP, Laurens S, Arliguie G, Breysse D, Garnier V, Dérobert X, Piwakowski B. Description of the general outlines of the French project SENSO – Quality assessment and limits of different NDT methods. Construction and Building Materials. 2012 35:131-8.

[24] Szilágyi K. Rebound surface hardness and related properties of concrete. PhD report, Budapest University of Technology and Economics: 2013.

[25] Rojas Henao LM. Ensayos de informacion y extraccion de probetas testigo en hormigones autocompactantes. PhD report, Universidad Politecnica de Madrid: 2012.

[26] Spalvier A, Hall K, Popovics JS. Comparative Study of Rebound Hammer, Nitto Hammer, and Pullout Tests to Estimate Concrete In-Place Strength by Using Random Sampling Analysis. Transportation Research Record Journal of the Transportation Research Board. 2017 2629(1):104-11.

[27] Qasrawi HY. Concrete strength by combined nondestructive methods simply and reliably predicted. Cement and concrete research. 2000 30(5):739-46.

[28] Hobbs B, Kebir MT. Non-destructive testing techniques for the forensic engineering investigation of reinforced concrete buildings. Forensic science international. 2007 167(2-3):167-72.

[29] ACI 228.1R-19. Report on Methods for Estimating In-Place Concrete Strength. American Concrete Institute, Detroit: 2019.

[30] Romão X, Gonçalves R, Costa A, Delgado R. Evaluation of the EC8-3 confidence factors for the characterization of concrete strength in existing structures. Materials and structures. 2012 45(11):1737-58.

[31] Luprano V, Caretto F, Labia N, Ciniglio G, Tatì A, Tundo A, Pfister V. Nondestructive test methods for evaluation of concrete: the case study of Punta Perotti (Italy). 11 DBMC International Conference on Durability of Building Materials and Components, Istanbul: 2008

[32] Ali-Benyahia K, Sbartaï ZM, Breysse D, Kenai S, Ghrici M. Analysis of the single and combined non-destructive test approaches for on-site concrete strength assessment: General statements based on a real case-study. Case studies in construction materials. 2017 6:109-119.

[33] Breysse D. Nondestructive evaluation of concrete strength: An historical review and a new perspective by combining NDT methods. Construction and Building Materials. 2012 33:139-63.

[34] Breysse D, Martínez-Fernández JL. Assessing concrete strength with rebound hammer: review of key issues and ideas for more reliable conclusions. Materials and structures. 2014 47(9):1589-604.

[35] Alwash M, Breysse D, Sbartaï ZM. Using Monte-Carlo simulations to evaluate the efficiency of different strategies for nondestructive assessment of concrete strength. Materials and Structures. 2017 50(1):90.

[36] Alwash M, Breysse D, Sbartaï ZM, Szilágyi K, Borosnyói A. Factors affecting the reliability of assessing the concrete strength by rebound hammer and cores. Construction and Building Materials. 2017 140:354-63.

[37] Pfister V, Tundo A, Luprano VA. Evaluation of concrete strength by means of ultrasonic waves: a method for the selection of coring position. Construction and Building Materials. 2014 61:278-284.

[38] Breysse D, Balayssac JP, Biondi S, Corbett D, Goncalves A, Grantham M, Luprano VA, Masi A, Monteiro AV, Sbartai ZM. Recommendation of RILEM TC249-ISC on non destructive in situ strength assessment of concrete. Materials and Structures. 2019 52(4):71.

[39] Alwash M, Breysse D, Sbartaï ZM. Non-destructive strength evaluation of concrete: Analysis of some key factors using synthetic simulations. Construction and Building Materials. 2015 99:235-245.

[40] ACI 214.4R-10. Guide for Obtaining Cores and Interpreting Compressive Strength Results. American Concrete Institute, Detroit: 2010.

[41] Pereira N, Romão X. Assessing concrete strength variability in existing structures based on the results of NDTs. Construction and Building Materials. 2018 173:786-800.

Highlights

- Concrete strength estimation is based on limiting the risk of a wrong assessment
- The main features of concrete strength estimation are analysed by synthetic simulations
- The effect of several parameters on the strength assessment quality is analysed
- The effect of conditional coring is highlighted and quantified.
- The methodology defining the number of cores for a given target accuracy is presented

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: