NDT Inspection Strategy to Minimize the Number of Samples for On-Site Concrete Evaluation

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Abstract
Non-destructive testing techniques (NDT) are essential to investigate structures in order to assess properties or detect anomalies (cracks, pathologies, etc.) in concrete. Due to budget limitations, an optimal methodology to estimate the integrity of a structure with a minimum cost is required. Destructive tests (DT) would eventually be necessary to corroborate the information obtained by NDT. This paper presents an efficient strategy to establish an NDT campaign for reinforced concrete structures. The aim is to assess concrete porosity and saturation degree by a spatial optimization of NDT measurements and cores to extract. For placing in an optimal way the cores to extract, studied properties values obtained by destructive tests were used. They were obtained after the fusion of three NDT techniques (capacitive method, impact echo and electric resistivity). This spatial optimization is made by the optimization spatial sampling method (OSSM) and is based on the spatial correlation of properties. Some results obtained on a wall in CEA-Saclay – France are presented.

Keywords: Non Destructive Testing (NDT), monitoring, concrete structure, optimization, spatial variability, data fusion.

1. Introduction

Non-Destructive Testing (NDT) techniques are essential not only for detecting anomalies, but also for assessing the properties of concrete and their spatial variability during the diagnosis of civil engineering structures. NDT is a powerful tool for reducing the auscultation budget of a work of art. The proposed approach is included in a national project which goal is to optimize the monitoring of civil engineering structures by implementing preventive maintenance to reduce costs. The approach incorporates the use of probabilistic models to predict the evolution of the structure between two auscultation campaigns. The model input data is durability indicators as the saturation degree, porosity, etc., which are obtained either by the fusion of NDT or destructive tests (ED). These durability indicators must be optimized to minimize the number of measurements and thus minimize costs.

In the case of this study, for the pre-auscultation, NDT fast techniques allow to obtain an overall view of the spatial distribution for a particular property of the concrete (ex: compressive strength, porosity, saturation degree, etc.). Then, an additional study with higher quality techniques can be performed in the critical areas identified by the first stage. They are sensitive to the same properties but they are often of long implementation and exploitation. This approach allows an efficient characterization of the property based on the contributions of both NDTs and as a consequence the cost is reduced.

However, to have a maximum profit on a high quality NDT in an already pre-auscultated structure, it is necessary to also use an optimal spatial sampling method to reduce the number of auscultation points. For this purpose, the most commonly used is the spatial simulated
annealing algorithm (SSA) [1]. Although this procedure is regularly used in geostatistical applications [2] and in other areas such as radioactive waste [3], the study of ecosystems [4], etc, it has not been used on civil engineering structures. In this paper, an original optimization spatial sampling method (OSSM) [5] inspired on the SSA was tested with two complementary objectives functions: the mean prediction error and the variance estimation error (the error on the estimation of the variability). The performance of the OSSM was explored with non-destructive measurements taken on a wall of the CEA - Saclay, France.

2. Tools and methods

2.1 Spatial correlation and interpolation

The concrete heterogeneity involves the detection of spatial variability in the material during auscultation. However, most of the time, for a number of measurements distributed over a surface, those that are close in distance will have a certain similarity, while the more distant will be different. This spatial dependence can be represented as a statistical function known as the variogram [6].

Each experimental variogram can be modeled by the least squares method to obtain the parameters used later in the matrices required for spatial interpolation by the kriging method. Figure 1 shows an example of a spherical model adapted on the measurements of compressive waves velocity obtained by the impact echo test on the North Wall at CEA-Saclay (description of the work of art, paragraph 3). Three main parameters can be derived from this variogram: the nugget (C₀) which describes the variance for repeated measurements several times at the same point, the sill (C) representing the overall variance and the range (a) which represents the maximal distance where the data is correlated (correlation length).

![Variogram Vp_IE](image)

Figure 1. Empiric variogram and adjusted model with its parameters of the impact echo’s compression waves velocity measured on the North Wall on CEA-Saclay.

Kriging, which is a method widely used for spatial interpolation can predict unobserved measurements (Z *) using the weights of the surrounding observed measurements excerpted from the variogram parameters and assuming a constant mean [7].

2.2 Optimal Spatial Sampling Method (OSSM)

To better approximate the spatial distribution of the NDT measurements, an algorithm inspired by Spatial Simulated Annealing (SSA) was developed. This Optimization Spatial Sampling Method (OSSM) starts with an initial set “s₀” of n values distributed on a regular grid in a space S of N measurements organized in a regular grid “SO”. This set is
progressively modified by relocating one value of \( s_o \) to a random available location in \( S_O \). When the new configuration, \( s_1 \), is established, the fitness function is evaluated. This configuration will be accepted with a probability of acceptance \( P \) calculated with the step function described in (1):

\[
\Delta = J_o - J_1 \\
P = 0 \quad \text{if } \Delta \leq 0, \quad \text{.................................(1)} \\
P = 1 \quad \text{if } \Delta > 0,
\]

Where \( J_o \) is the objective function value for \( s_o \) and \( J_1 \) the objective function value for \( s_1 \). Essentially, the new configuration is accepted if \( P = 1 \) and refused if \( P = 0 \).

Two fitness functions were tested for the optimization algorithm. They are defined below.

### 2.2.1 Mean prediction error (MPE)

This function is the mean of the prediction error, which is the absolute difference between the measured (\( Z \)) and the estimated (\( Z^* \)) values calculated across all the points \( n \), and normalized with respect to the average of the \( N \) original points (Mean_R).

\[
MPE = \frac{\sum_{n=1}^{N} |Z_n - Z_n^*|}{\sum_{n=1}^{N} |Z_n - \text{Mean}_R|} \times 100 \% \quad \text{.................................(2)}
\]

This function represents the error that is committed when attempting to represent the original measured field with a smaller number of measurements \( n \).

### 2.2.2 Variance estimation error (VEE)

This function represents the error in the calculation of the global variance with a smaller number of known measurements (\( n \)). Zero error means that the global variance calculated with \( n \) is the same as the global variance calculated with the \( N \) original measurements. Thus, the VEE is evaluated as one minus the ratio between the variance of \( n \) known measurements (\( V_i \)) and the variance of the \( N \) original measurements (\( V_N \)).

\[
VEE = 1 - \frac{V_i}{V_N} \times 100 \% \quad \text{.................................(9)}
\]

### 3. Validation of the OSSM on a case study: CEA-Saclay

#### 3.1 Spatial sampling design for NDT measurements: Impact Echo and Capacitive method

CEA-Saclay is one of the studied sites selected for a French national research project (EvaDéOS). The interest of this site is that the concrete is sufficiently high carbonated with relative depths close to the coating thickness. The case study considers two walls: one facing north (Wall N) and the other facing south (Wall S). These walls were built in 2004, their lengths vary between 20 and 40 m and its height is approximately 2.2 m. Figure 2 shows the location of the walls inspected as part of this project.
The industrial approach of concrete assessment implies to reduce the number of NDT tests and cores to optimize the auscultation cost. For this study, the wall N was selected. Many NDT techniques were used in this measurement campaign, but only the measurements of the permittivity of the capacitive method (P_Capa) and the compression wave velocity of the impact-echo technique (Vp_IE) were used and analyzed here to validate the approach developed.

For being able to do this, a series of 28 capacitive and impact echo measurements were made for the pre-auscultation of the wall N. They are distributed along two parallel horizontal lines. A spherical variogram was fitted to P_Capa and Vp_IE experimental data. The fitted curves have a nugget of 0.02 and 0 (m/s)², a range of 0.6 m and 0.51 m and a sill of 0.24 and 8894 (m/s)² respectively.

The OSSM performance was explored with different number of measurements (n). Figure 3 shows the variation of the two objective functions - MPE (Figure 3a and Figure 3c) and VEE (Figure 3b and Figure 3d) – with n measurements organized on a regular grid (before optimization) and with the optimized location of those n measurements organized on an irregular grid (after the OSSM) for P_Capa and Vp_IE.

If MPE is used as the objective function, we can observe a significant decrease in its value for P_Capa (Figure 3a) of 49% on average from a regular grid to an irregular one. In the case of Vp_IE (Figure 3c), there is a decrease in average of 55% for MPE. From Figure 3b, it can be deduced that if n is reduced to 13, the new global variance is equal to that obtained with the original 28 measurements P_Capa.
Figure 3. Relationship between the number of measurements and the fitness function values for a) MPE (P_Capa), b) VEE (P_Capa), c) MPE (Vp_IE) and d) VEE (Vp_IE). Regular grid (blue points) and optimal irregular grid (red points).

We can visualize better the impact of the optimization from Figures 4a to 4d. Figure 4a shows the original map with 28 Vp_IE measurements, Figure 4b shows the kriging map obtained with 13 measurements organized in a regular grid, Figure 4c shows the kriging map obtained with 13 measurements organized in an irregular grid optimized by the algorithm with MPE as the objective function and finally, Figure 4d shows the kriging map obtained with 13 measurements arranged in an irregular grid optimized by the algorithm with VEE as objective function.

Figure 4. a) Original Vp_IE map with 28 measurements, b) Kriging map made with 13 measurements organized in a regular grid, c) Kriging map made with 13 measurements organized in an optimal irregular grid obtained after OSSM with MPE as fitness function, d) Kriging map made with 13 measurements organized in an optimal irregular grid obtained after OSSM with VEE as the fitness function.

MPE and VEE showed interesting performances. Their value is reduced by 52% and 75% on average for both NDT techniques going from a regular grid to optimal irregular one. Note that MPE leads to a smaller mean prediction error in the kriging map and a mean value closer to the original one than the mean obtained with VEE. On the other hand, VEE provides a variance value closer to the global variance than MPE. In this case VEE and MPE gave an
almost identical kriging map. However, special attention should be paid to what is expected before selecting the most appropriate objective function to analyze a particular data set. For example, if the structure manager wants to know the spatial distribution to optimize further controls or he wants to locate the priority zones to schedule maintenance, MPE must be used. If, on the contrary, he wants to estimate the overall variability of the material for reliability calculation, VEE should be chosen. Since the aim of our work is to optimize the monitoring of civil engineering structures by NDT methods, MPE will be privileged in the follow-up of the study.

3.2 Spatial sampling design for destructive testing

As part of a complete and reliable inspection, destructive laboratory testing on concrete samples obtained by coring is needed to confirm and calibrate the results of the properties obtained by the fusion of different NDT techniques [8]. Because of the coring and destructive testing cost, and a possible damage to the structure, it is important to build an optimal spatial sampling plan to extract a limited number of cores.

In this study, the objective is to place the best way possible the cores to extract, to make destructive tests to obtain the saturation degree and porosity for each core. In order to do this, ideally we should have the measurements of saturation degree and porosity for each auscultation point to use the OSSM. However, as mentioned before, it is not practical to take 28 cores. Therefore, we combined the capacitive method, impact echo and electrical resistivity through a fusion process based on the theory of possibilities [9] to obtain the reference maps for saturation degree and porosity at each point of the auscultated wall. It is assumed that these reference maps have a similar spatial variability from the ones that would be obtained if we had made destructive tests for 28 cores extracted in each one of the auscultated points. Only 25 points were selected for the OSSM implementation due to the non-destructive measurement errors identified in the process of inversion and fusion.

For each one of the concrete properties (degree of porosity and saturation degree), a variogram was determined. As shown in Figure 5a, a spherical template with a range of 0.18 m, a sill of 38.9% and a nugget of 0% has been fitted to the saturation degree data. In contrast, for the porosity, no model could be fitted (Figure 5b). This means that the distribution of the porosity throughout the wall is constant. Hence, the porosity cores can be located at the same positions as the ones obtained after OSSM made for the saturation degree with MPE and VEE as fitness functions. We can see from figure 5 that if the NDT data have a sort of correlation and a variogram, concrete properties do not necessarily show the same spatial correlation. This can be due to the dependency of NDT to more than one concrete property. However, this multiple dependency is reduced after using inversion and fusion.
For this approach, it was used two objective functions: MPE_Sr and VEE_Sr for the saturation degree. We study this minimization for different number of cores. Figures 7a and 7b show the evolution of each objective function according to the number of cores organized in a regular grid before optimization (blue curve), and in the case of an irregular grid after optimization (red curve). The advantage of this transition to an irregular grid is to give an additional degree of freedom in the grid to reduce the objective function value.

It is noted on the figures 6a and 6b that the error decreases to 24% and 45% in average from a regular grid to an irregular one for the case of OSSM with MPE_Sr and VEE_Sr respectively. However, although the location of the cores on an irregular grid decrease the error significantly, the decrease is not as important as in the case of spatial optimization of NDTs. It can be expected due to the reduced number of cores (known values).

Figure 7 shows an example of the optimization with 5 cores. In the left part of the figure, we have the reference maps for saturation degree and porosity obtained after fusion. In the middle part of the figure, we have the kriging maps for saturation degree and porosity after optimization carried out with 5 cores and MPE_Sr as the objective function. Finally, at the right part of the figure, we have the kriging maps for saturation degree and porosity after optimization carried out with 5 cores and VEE_Sr as the objective function. In the figures, it can be seen clearly the objective of each fitness function. Even though the number of cores is only 5, the kriging maps obtained with the locations obtained after OSSM and MPE_Sr as the fitness function for both reference maps (Sr and P) are quite similar. Moreover, when VEE_Sr is used as the fitness function, it is notable that the optimized locations search to find the maximum and minimum zones. Besides, using the exact same locations for Sr and P, optimizing only the locations of Sr, confirms that the variability of the porosity is constant. Hence, satisfying results for Sr and P can be obtained with the optimization of only Sr core locations.
4. Conclusions

This study provides an approach that can contribute to effective characterization of structures by implementing NDT techniques with the aim of limiting inspection costs. A preliminary study of a concrete structure was carried out with two non-destructive testing techniques (capacitive method and impact echo) to evaluate the spatial correlation of a wall on the CEA site in Saclay, France. A first spatial optimization was made for later use in the case of a future auscultation with more performant NDTs or for a monitoring of the site. Then, the fusion of three NDTs (capacitive method, impact echo and electrical resistivity) is made by the theory of possibilities method to obtain the saturation degree and porosity values for the studied wall. After the fusion of the non-destructive measurements and the estimation of the two studied concrete properties, variogram models could be fitted only for the saturation degree. This variogram was then used for the spatial optimization of the cores to extract for the studied wall.

For NDT spatial optimization, two objective functions have been exploited: MPE and VEE. However, for cores to extract case, spatial optimization using only MPE and VEE for Sr as the objective functions were retained because no variogram model could be fitted for P, which means that its variability is constant throughout the studied wall. NDT optimization was tested with twenty-three, eighteen, thirteen, eight and three measurement points. All cases showed a decrease of the objective functions: 52% for MPE and 75% for VEE on average. Between regular and irregular spatial distribution of measurements for spatial optimization for destructive testing samples (cores), the algorithm was tested with five, four, three and two cores. The algorithm was run with MPE_Sr and VEE_Sr as fitness functions. All cases showed an important decrease of objective functions, but not as important as the NDT case. This can be explained, by the reduced number of cores.
Other works are proposed in this study in order to improve the algorithm like the inclusion of a cost function as an alternative objective function. We plan to use the algorithm in a three-dimensional space to include a new parameter which is the penetration depth of the non-destructive techniques that could provide information on the state of degradation in depth of the structure. Indeed for now, it is assumed that the ND measurements are made for an average concrete thickness.

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6. References


