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SPATIAL DEGRADATION IN RELIABILITY ASSESSMENT OF AGEING CONCRETE STRUCTURES

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Abstract. *Presented paper concerns the difficulty of objective characterization of spatial variability due to advancing degradation as a result of environmental exposure. The main issue is to enhance realism in the prediction of remaining service life of existing concrete infrastructure and thus effectively cover the relatively large sample space of possible future deteriorating states. This is done by introducing a special sampling strategy where artificial realizations of damage scenarios are generated. Here, not only material and geometry of a particular structural member is randomized in a nonlinear 3D finite element context, but advanced evolutionary spatial degradation models are applied to account for the variability of future damage states. These are computed using a non-traditional evolutionary scheme based on cellular automata (CA), which is used here to solve the transport equations in time and space and generate the irregular and heterogeneous structure of concrete. Within the presented example of an ageing bridge, the CA simulation also accounts to complex boundary conditions, e.g. the non-stationary seasonal de-icing salt application, irregular turbulent feed or washout effects. The selected case study of an existing deteriorated bridge serves as an application example with historical evidence and well documented damage profiles. It is further discussed with respect to Monte Carlo based structural reliability assessment, how to infer likelihoods associated to the set of implicit statements on damage, as this concept still offers open questions for research, yet is critical to successful and objective uncertainty quantification.*

1 INTRODUCTION

An increased demand over the last two decades in developing procedures for statistical estimates of remaining service life of aged reinforced and pre-stressed concrete structures and infrastructure, of which many are still in use due to socio-economic constraints, has prompted research into methods for codification of reliability based performance indicators for existing structures [1]–[3]. Furthermore, life cycle assessment approaches in civil engineering attempt to extrapolate such criteria in time while applying rather strong assumptions regarding the statistics of load intensity at the end of the reference period. Not surprisingly, this results in rather large multidisciplinary task comprising many uncertainties, both epistemic and aleatory [4]. In order to solve it, one must clearly reduce the underlying complexity to a certain extent. The levels of such simplifications and their respective implications are among the topics of this paper, together with review on current and future state of research on the relevant concepts, central to which is a deteriorated structure subjected to nonstationary mechanical and environmental loading [5], [6], and incomplete or imprecise reference to the original (undamaged) structural system due to missing or vague documentation drawings, as discussed e.g. in [7], [8].

In an attempt to capture the future development of safety and reliability of any structure, a decision has to be made over the variety of available performance indicators. The general approach for safety evaluation of existing structures is based on codes and different specific regulations. It has been found that reliability assessment, when applied to bridges and beyond the boundaries of codes, can bring significant money savings and provide a new insight into the administration of structures and decision making process [9]. By reducing the margin of error in design, on the other hand, caution must clearly be exercised when applying complex or abstract models of reality in inference and prediction, and the effects of basic random variables must always be considered together with model uncertainty [10], [11].

In the context of herein discussed topic of aging structures the artificially generated realizations of deteriorated structures [12] are solved by methods of stochastic nonlinear fracture mechanics [13] in an attempt to provide reliability indexes for various concepts of probability-based performance indicators [3], [14].

The computational cost of such as task is extensive. However, among the tradeoffs are the features like derived global safety factors for nonlinear analyses, various contributing failure modes, capturing long term effects and durability aspects. Knowledge on the two latter is essential for life cycle interventions, while the two former are needed for safety related considerations. It should be noted here that in order to capture the effects of random scalar input variables, the estimation of coefficient of variation of the structural response can be based on two analyses only, each representing a certain percentile p (e.g. 5 p and 50 p) of the random variable distribution function [15]. Then by assuming a particular two parameter probability distribution function the mean and variance can be computed and consequently used for limit state formulations.

While this approach was proved to be effective by e.g. [16], [17] for randomizing the scalar input variables, the effect of spatial variability on structural response can only be described for complex boundary conditions by Monte Carlo (MC) based simulations [18]. Among the available schemes for reducing such high-dimensional computational task there are reduced-order models of finite element approximation of the problem [19], [20] and methods for reducing the number of required MC samples by introducing special sampling techniques, such as Importance Sampling (IS) [21]–[23], Latin Hypercube Sampling (LHS) [24], [25] and other approximation techniques [26], [27]. While many variations of such techniques exist for both static and dynamical systems, until now there has been a limited effort or success according to authors knowledge to formulate a special sampling that would enable to effectively sample from finite sets of realizations involving stochastic spatial variability.

One of such formulations published in [6], [28] offers a promising concept for applicability in the presented context. In this work critical realizations of stochastic processes are successfully identified by using pattern recognition and image processing techniques to compute a correlation pattern which is used for ranking of the individual samples according to expected response quantity. Although the original work aimed at classifying artificial samples of oscillatory stochastic processes sampled in time domain, such as ground motion events, it is believed to be applicable in the context of this paper due to the fact that the processing itself was based on comparison of frequency domain transforms, such as rasterized evolutionary spectra [29] objects. In a similar way, the samples of spatially variable structural models both in 2D and 3D could be classified according to their importance.

In the following, authors will introduce a novel method for generating artificial samples of damaged structural components or entire structural systems in order to cover the sample space of possible deterioration progress in time from current damaged structure according to known damage profiles from inspection. The spatial variability patterns are generated and consequently solved by a non-traditional numerical approach based on Cellular Automata (CA) [30]–[34] and reflect the realistic environmental action in time and space together with the inherent variability of the initial state.

2 DAMAGE BASED PERFORMANCE INDICATORS

Despite been widely recognized and accepted, the considerations of spatial variability of mechanical or chemical properties are still rather limited [35]. Among the possible implications are underestimated variance of global resistance, or even worse, reduced resistance, which could also be attributed to size effect, a phenomena closely related to scaled spatial variability and studied intensively by [36]–[38]. The quantified effect of spatial variability on the statistical scatter of concrete structural response under typical operating conditions can be transferred via reliability based performance indicators [12], [14], [39].

Degradation processes are closely linked with robustness issues, maintenance strategies and hence with the remaining lifetime tR of structures [40], [41]. As such, these should receive attention from the respective authorities and interest from the scientific and engineering community. There exist several interpretations for system redundancy and robustness. The *redundancy* (from Latin *redundare* ”to overflow, to abound”) of a system accordingly defines the multiple presence of functionally identical or similar technical resources (load reserves) and the ability of the system to continue to carry load after the capacity of individual members is exceeded or even after the removal of individual members from the system. According to [42], *redundancy* is defined as the capability of a system to redistribute and increase loading processes after the failure of one main member. As a provision of capacity, a redundant structure has additional structural capacity and reserve strength, allowing it to carry a higher load than anticipated when considering the capacity of individual members. The measures of redundancy are [14]:

$$R_u = LF_u / LF_1 \tag{1}$$

$$R_f = LF_f / LF_1 \tag{2}$$

$$R_d = LF_d / LF_1 \tag{3}$$

where: LF_1 is the load that causes the failure of the first member, LF_u is the load that causes collapse of the system, LF_f is the load that causes the functionality limit state of the initially intact structure to be exceeded and LF_d is the load factor that causes the collapse of a damaged structure which has lost one main member. An alternative definition associated with the redundancy of a system was also given in terms of the reliability index using a "redundancy factor" β_R by:

$$\beta_R = \frac{\beta_{int.}}{\beta_{int.} - \beta_{damaged}} \tag{4}$$

where $\beta_{int.}$ is the reliability index of the intact structural system and $\beta_{damaged}$ is the reliability index of the damaged structural system. Note that his type of analysis can only be implemented in cases where appropriate data regarding the potential hazards (actions, degradation) and their statistical description in time and space are available and where the system reliability indices associated with these events can reliably be determined. The latter statement implies that such concepts are currently not applicable to common engineering practice since methods for reliable determination of reliability indexes are not available when effects of random input variables and spatial variability are to be considered.

The overview of available and relevant features of general-purpose software for structural reliability analysis are described in [43] and well suited experimental tools for reliability assessment of existing damaged engineering systems are described e.g. in [44]–[46].

The second term commonly used in connection with system reliability is that of *robustness*. The term of *robustness* (Latin *robustus*, adjective of *robur* "oak, very hard wood") denotes the ability of a system to withstand changes without having to adapt its originally stable structure. Examples are the robustness of a system against overloading or its robustness against a decrease in load carrying capacity of individual system elements. Robustness can be considered according to [47] as the capability for performing without failure under unexpected conditions and as a quantitative evidence can be defined on the basis of the following robustness index:

$$RI = \frac{P_{f\,damaged} - P_{f\,intact}}{P_{f\,intact}} \tag{5}$$

where, $P_{f,damaged}$ is the probability of failure of a damaged structure and $P_{f\,intact}$ is the probability of failure of the intact structure. Obviously, the *RI* would equal 0 for a robust structure and may approach infinity for a non-robust structure. In addition, implementable measures of redundancy and robustness were advanced by the offshore industry in the ISO 19902 standards. One of those measures is the Reserve Strength Ratio (RSR), which is defined as:

$$RSR = \frac{Q_{ultimate}}{Q_{design}} \tag{6}$$

where $Q_{ultimate}$ is the load capacity of the structure and Q_{design} is the unfactored design load. Another measure is the Damaged Strength Ratio (DSR) defined as:

$$DSR = \frac{Q_{damaged}}{Q_{design}} \tag{7}$$

where, $Q_{damaged}$ is the load capacity of a structure which is damaged due to corrosion or fatigue failure. More details with respect to performance formulations for ageing infrastructure are provided e.g. in [12].

3 SPATIAL VARIABILITY AND STRUCTURAL RESPONSE

Among the typical spatially correlated random quantities of interest relevant to structural analyses of civil structures and infrastructure are geometric perturbations (node coordinates, shell thickness), material properties (composite components at micro and macro scale), damage (steel depassivation, cracks), loading (temperature, diffusive attack of chloride ions). These all contribute by some extent to the overall variability of structural response, together with the FE model uncertainty and scalar (vector) random input variables. In case of stochastic static analysis, the effects of stochastic temporal processes representing the load components (traffic, wind, ground acceleration) is reduced to a vector representing a particular time instance. In case of stochastic structural dynamic analysis, on the other hand, the effect of spatial variability is typically neglected and the stochastic loading process is modeled in time. Current computational resources, including scientific clusters [48], still represent a barrier in front of stochastic simulations [49] for both spatial and temporal variability. There are few theoretical exceptions, however, where (I) effective sampling for coupled temporal and spatial variability can be applied (unfavorable conditions can be deduced from deterministic study of the problem, such as strength of material or impact force), (II) the interest is to answer what-if-scenarios or simply show importance of such considerations in practice and (III) stochastic simulation is used to numerically proof a hypothesis (based on e.g. limit theorem).

For example, [50] have demonstrated how spatial variability in 2D structural static stochastic FEM can simulate the combined statistical-energetic size effect at a particular size range, besides the conventional estimation of statistical moments of structural response.

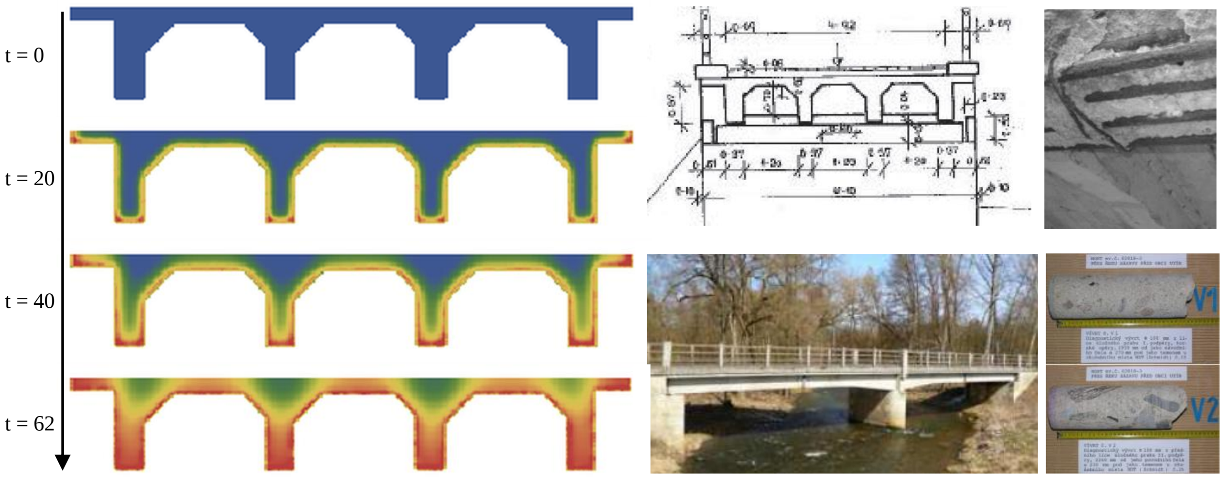

Figure 1: Particular realization of CA simulation reproducing the temporal evolution of irregular corrosion-prone zones (left) on an existing deteriorated bridge. The problem of available evidence is schematically depicted by original documentation drawings (intact system inference), core samples and current damage (t=62 years).

By accepting certain assumptions [51], [34], [12], it is possible to characterize the time component of spatial variability due to advancing degradation of aging reinforced and prestressed concrete structures, such as bridges, for structural static analysis by adopting the proposed generator of artificial damaged scenarios. Here, the evolutionary algorithm ensures that the resulting patterns of variability corresponds to actual progress of degradation by imposing realistic boundary conditions (e.g. nonstationary stochastic oscillatory temperature loading or deicing salt application) together with local interactions based on actual physics or chemistry. The illustrative application example (fig.) concerns an existing bridge, which has been built in Czech Republic in 1953, is currently severely damaged and under replacement/rehabilitation assessment.

Furthermore, microstructure generator based on the same technique can be used to account for the inherent spatial variability of concrete at micro scale by constructing the initial irregular grid that captures the two component microstructure (aggregates and cement paste) of concrete by applying certain elementary rules in a number of time step, ensuring a realistic pattern of components distribution.

The resulting set of such artificial realizations can be further analyzed by using the probabilistic tools described in the remaining part of this paper and reduced by the proposed identification framework.

4 DEGRADATION MODELING IN TIME AND SPACE

The early deterioration of concrete structures due to the effects of external aggressive environment is well known, as well as the amount of variability concrete specimens and structural systems exhibit due to aggregate orientation, size, shape and ratio. The magnitude of the influence of these microstructural differences on the composite's properties will result in a scatter of response characteristics, such as load displacement curves or crack propagation. In order to reduce the prohibitive computational cost of coupled stochastic simulation of local aggregate effects, long-term dynamic environmental exposure and structural response, the so called damage scenarios are generated as input for the repeated structural static analysis such that the time component is inherently included by adopting the evolutionary paradigm of Cellular Automata (CA). The suggested numerical approach is derived in a bottom up fashion following the cellular paradigm. Main characteristics of such discrete system are parallelism and uniformity leading to transparent and robust computational scheme. Conventional approaches to diffusive processes modeling, such as finite element method (FEM) or finite difference method, may resemble the cellular automata (CA) model in some aspects, however, the top down nature of these methods, unlike the CA, leads to the common discrete-to-continuum-to-discrete paradox [52].

The lightweight formulation of the diffusion process by means of neighborhood processing enables to include various non-diffusion related phenomena, such as electrochemical (corrosion) or structural (cracking) effects. The suggested CA approach enables for comprehensive temporal and spatial simulation of harmful substances propagation, while respecting various conditions and mechanisms, such as turbulent feed effects due to passing traffic (bridges), surface washout effects (rain), seasonal application (de-icing salt application), and the influence of initial microstructural differences of individual realizations, among other. Such irregular lattice (concrete microstructure topology) can be generated within the CA paradigm by the proposed cluster generator or extracted from photo documentation by means of proposed transfer algorithm [34]. Alternatively, if there is insufficient evidence, the simulation topology can be considered as initially uniform and the evolutionary components Φ of the redistribution scheme for a particular cell X in the successive time step t+1, eq. (8), can be randomized for each or selected time steps within the explicit time stepping scheme

$$X_{(t+1)} = \Phi_1 X_t + \Phi_2 N_t + \Phi_3 E_t + \Phi_4 S_t + \Phi_5 W_t \tag{8}$$

while satisfying the standard normality rule (eq. 9) within a particular neighborhood scheme (e.g. Von Neumann (fig. 2) or Moore), as CA rules are defined locally and the spatial region must be specified for a cell to gather information from its vicinity when updating its state.

$$\Sigma\ \Phi_i^t = 1 \tag{9}$$

In eq. 8 the discrete variables {Xt , Nt , Et , St , Wt} represent the state values of neighboring cells (North, East, South and West analogy) according to Von Neumann's neighborhood scheme in two dimensions and unity radius. Note that in isotropic case the values of Φ 1=0.5 and Φ {2,..,5} = 0.125. In the suggested approach to topological effects, the user defines the ratio between the bond (aggregates) and fill (cement paste) cells. The overall diffusion coefficient D may be expressed by such formalism:

$$D = \Phi_1\ \Delta x^2\ \Delta t^{-1} \tag{4}$$

where Δx is the cell size and Δt the time step duration length.

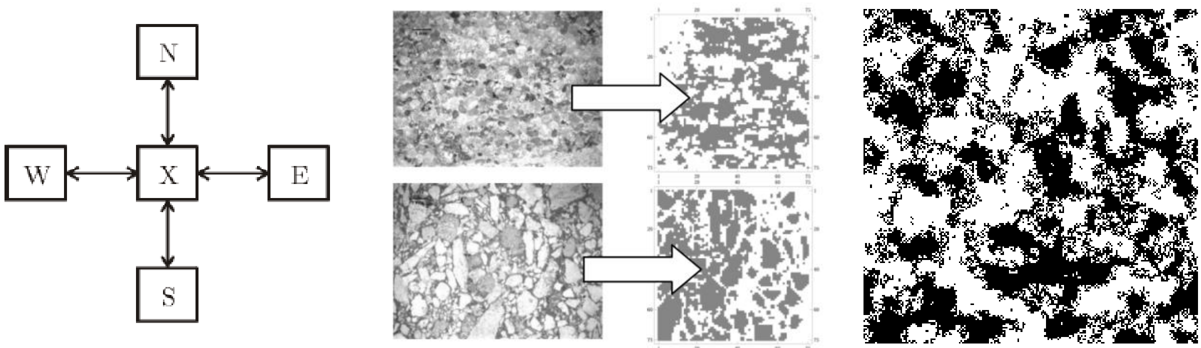

Figure 2 Von Neumann's neighborhood of a single cell and unity radius (left), image to CA lattice mapping (middle) and outcome of CA based microstructure generator (right).

The briefly introduced procedure above is described in detailed in [51] and in the broader context of this paper serves as an abstract reduction to simulate the chain of actions leading to reduced serviceability, life cycle and load bearing capacity of concrete structures, starting e.g. at local depassivation (loss of protective function of concrete) of exposed steel members, such as reinforcing bars or prestressing tendons, and leading to severely damaged structures, safety of which is the central concern of this probabilistic framework.

Moreover, current standards require minimum concrete cover thickness, which calculation is, among others, based on the given level of environmental exposure. The amount of concrete used as a protective layer significantly affects the cost, reliability and service life of the structure and for realistic estimate, such task requires the utilization of stochastic techniques [53] in order to quantify the effect of spatial variability and initial heterogeneity.

5 INTEGRATED FRAMEWORK FOR STRUCTURAL RELIABILITY ANALYSIS

The field of structural reliability has expanded during the last four decades from narrow academic discipline. Originally, researchers focused on modeling and analysis of small idealized structural components. Currently, it has become a basis for evaluation of limit states and performance of complex structural systems, such as buildings or bridges. It is also acknowledged for providing quantitative feedback between structural engineering and its social consequences [54]. The evolving paradigm of performance based design has also contributed to increasing demand for structural reliability software.

The existing software platforms enable randomization of structural loads, material properties and geometries for design, decision making and assessment of deteriorated existing complex systems. In general, the capability to model correlated random processes (e.g. spatially or temporally fluctuating properties of both action and resistance models) is still very limited [43], unlike the commonly randomized scalar random input variables. The random field concept in probabilistic modeling is effectively utilized in the multipurpose COSSAN (COmputational Stochastic Structural ANalysis) package [44] and in the SoS (Statistics on Structures) add-on tool to optiSLang (the optimizing Structural Language) [46]. In order to incorporate non-stationary stochastic process or time dependent event boundary, the Sesam probability module - Proban (General Purpose Probabilistic Analysis Program) can be used [55].

The reason why most software platforms for probabilistic-based assessment of engineering structures avoid randomization of non-scalar (and vector) properties is due to the requirement on the low number of samples. In case of structural static problems and scalar random input variables, the sample reduction schemes for low probability MC simulations are well established and offer reasonable cost of accuracy [56]. In case of nonlinear structural dynamics, the computational cost is still prohibitive even for random scalar input variables. If the objective now is to include the effects of correlated random process in time or space, the required number of samples for the brute-force MC simulation and engineering failure probabilities would be clearly prohibitive. Such processes are utilized frequently on a possibilistic basis by sampling from the design space and quantifying the effects of individual realizations without attempting to assign probability of such events. Such approach is valuable for demonstrating the importance of spatial variability and size effect [37], [38], [57], [58].

Note that many correlated random processes relevant to structural analysis of deteriorated components or entire structural systems should in fact represent an outcome of combined phenomena, such as e.g. environmental action (damage scenarios). In such case, the associated likelihoods of combined effects are initially unknown or cannot be determined by any known model and estimates of posterior distributions can be based only on a rather strong assumption of uniform prior.

In the context of spatial degradation phenomena in a small sample MC-based reliability assessment of ageing concrete structures the following statements appear to be useful for development of integrated framework for structural reliability analysis.

- Overall system behavior has to be captured by a comprehensive FEM analysis with emphasis on geometrical details (e.g. precise reinforcement definition), durability aspects (cracking) and realistic behavior. Suitable tool is e.g. the ATENA software package which proved effective in many studies and practical applications in the past two decades, as detailed e.g. in [12], [59].

- Monotonous time dependent behavior such as creep, shrinkage or reinforcement depassivation have to be included. An extensive collection of analytical formulations for point-wise concrete degradation phenomena is given e.g. in [60].
- Safety margins have to be expressed globally, as described e.g. by [16].
- Finite set of spatially variable samples for the original MC task can be generated according to available evidence (damage profiles) and driving mechanisms. The size of such set should reflect the expected first passage probability. For a feasible small sample MC simulation a special sampling strategy proposed by [28] can be utilized in order to sample representative realizations from the original set according to computational resources available and required confidence [6].
- A selection of damage based performance indicators can be used for alternative results interpretation and possibly more effective risk communication.

An ideal software platform for solving such task will have to reflect the rapid development across the associated disciplines and therefore will unlikely have the form of a closed commercial solution offered by a single company. A collection of extendable modules and communication interfaces initially designed for parallel computing and offering access to well established commercial FEM codes as well as open source projects from the academia seems more appropriate and probable for the near future.

6 ASYMPTOTIC PROPERTIES

Let us consider within the context of this paper e.g. a two dimensional (2D) finite space upon which a randomly distributed property (mechanical or chemical) will be generated according to an arbitrary concept (cross correlated random fields) or generator (e.g. the proposed CA scheme).

Within a continuum theory there are infinite different realizations possible. For a stochastic MC simulation whose objective is to reproduce the tail regions of structural response distributions (low-probability events) this is not practical for several obvious reasons.

1. Prior statements regarding the asymptotic behavior is impossible for such spatially variable system with the exception of few very simple examples, where deterministic analysis of the problem is possible [61]–[63].
2. The continuity within finite space leads in theory to infinite samples.
3. No effective sampling strategy exists for covering such design space.
4. Large variance can be expected for conclusions based on repeated small sample MC simulations, with or without special sampling design.

In practice, however, the finite space in 2D can be discretized into finite areas (regions, elements, cells, etc.), regular or irregular, for each of which the random property is assigned in a way that no overall important feature is lost due to such transform. For concrete, this corresponds, according to expected outcome of the experiment, to e.g. mesoscale, microscale or macroscale, as for example is detailed in [64]. In such case, the finite space is divided into a finite number of regions and the previous problem of stochastic MC simulation can be summarized as below.

1. A finite number of spatially variable combinations (configurations) exists.

2. The problem of asymptotic behavior is transformed into finding the most extreme realizations (for first passage probabilities) or finding the moments of probability distributions based on samples from effective patterns*).
3. The total number of realizations results from pure combinatory. For example, consider the different arrangements of 1024 x 768 pixel screen if the color of a single pixel is determined by mixing 3 RGB values, ranging from intensity of 0 to 255, where the. Clearly, the total number of different "images" one may observe at such screen would be $256^{3\cdot 1024\cdot 768}$. Similarly, in case of the pattern representing a two component system from fig. 2 left, the total number of patterns would be $2^{350\cdot 350}$ given a square grid of cells of length 350. Note how binary characteristic of the state values can reduces the overall dimensionality of the problem.
4. The effective number of realizations could be lower due to the fact that not all realizations possible are relevant. In order to demonstrate this fact let us consider the problem of discretized cross section of the same concrete specimen (fig. 2left), whose mechanical properties are to be investigated in a numerical probabilistic manner. The arrangement of the bond (cement paste) and fill (fractions of stone) can be attributed to certain expectations, where the knowledge of the actual mixing and casting of concrete is reflected.
   a. For example one may apply a set of filters that would discard all patterns not resembling concrete inner structure. Such filters could utilize e.g. contrast gradients to detect lines and higher hierarchy objects (morphological analysis). Note that this approach would be the least efficient, since generating the total number of realizations represent prohibitive computational burden, even for current computing technology.
   b. Another option would be to utilize one of established methods for generating the cross correlated random fields with a particular characteristic length. The effective number of realizations be estimated only and corresponds to the sum of non-repeating patters. Note that the user has limited control over the particular features of the generated pattern.
   c. One may as well generate the cross section by using the proposed evolutionary algorithm where arbitrary rules (simplified and possibly coupled laws of physics or mechanics) applied locally ensure that the evolving patterns corresponds to spontaneous, chaotic, self-similar concrete microstructure, and that no regular, organized, systematic or other non-representative pattern is returned. The number of effective realizations can only be estimated and corresponds to the number of non-repeating patters.

*) The exact solution to the discretized system exist and can be effectively approximated by special MC simulation proposed by [6] where one pre-samples from the effective sample set (training samples), then compute the correlation pattern, apply this correlation pattern to the original effective sample set and identify the patterns that suggests particular levels of importance. For the first passage probabilities, only the highest importance levels are relevant for analysis. To obtain the distribution moments, one can sample in a way that all levels of relevance are equally represented in the reduced sample set.

It is also important to note that the importance in discarding the “unrealistic” realizations, or in other words sampling from the effective sample set only, lies in the fact that unrealistically high/low results are clearly omitted. As for example it would make a little sense to include a concrete specimen with a straight continuous transverse concentration of weak material properties to estimate statistical resistance in tensile for specimens casted according to current regulatory codes or, similarly, conclude large resistance from a small sample of notched 3-point bending test with large aggregate at the face of the notch.

Incorporating such extreme realizations (outliers) is important for objective probabilistic assessment, but at the same time, there is rarely enough empirical evidence for rational treatment of such events, when both associated form and likelihood are almost exclusively available in retrospect only, after major effect and initial surprise [65]. The same applies to the subject of non-stationary temporal loads, not treated by this paper in particular, but contributing to the broader challenge of predicting and managing the effects of clime change.

Nevertheless, only with sufficiently small target probabilities, such large-impact events can propagate into the effective sample sets by accordingly adjusting the filters or local rules as described in 4a and 4c. For detailed analysis and benchmarking of particular generators against real samples of microstructure, morpohological features of both sets could be effectively utilized in commercial packages such as [66], [67]. In such way, e.g. by ranking particular aggregate fractions according to size and shape, quantities in weak analogy to correlation length from random field concept could be characterized.

7 CONCLUSIONS

- While the reliability assessment based on stochastic simulations is going beyond the boundaries of codes and as such can result in less conservative condition grade, it is imperative to incorporate all components of uncertainty and variability into the overall assessment. In general, the effect of commonly included statistical description of concrete and steel parameters on the structural response variability can be relatively small compared to the effect of model uncertainty and spatial heterogeneity. This paper provides a framework for effective testing of such hypotheses in general.

- The implicit degradation states for repeated MC simulations can be effectively generated by the proposed cellular automata approach, where temporal and spatial variability of the harmful substance ingress is modeled realistically. Furthermore, microstructure generator based on the same technique can be used to account for inherent variability by constructing the initial irregular grid that captures the two component microstructure of concrete. As an equivalent to random fields, the evolutionary CA generator produces spatial patterns of bond-fill distribution that can exhibit more realistic spatial distribution by introducing elementary local rules resembling simplified laws of physics.

- This feature, together with stochastic modification of evolutionary coefficient, leads to increased (and more realistic) spatial variability of degradation, which in turn affects the structural resistance significantly, and consequently increases (in most cases) the overall variability of structural response. Asymptotic properties of such systems have to be investigated in more depth in order to utilize such concepts in practice, together with an effective sampling strategy.

- Furthermore, some derived structural performance indicators, such as probability based robustness, may exhibit non-monotonous course for some realizations, when particular combinations of magnitude and distribution of damage (or spatial variability in general) lead to beneficial redistribution of load and increased structural resistance. In case of existing deteriorated structures, such effect can be attributed to loss of some pre-stressing tendons.

- The objective of enhancing realism in the prediction of remaining service life of existing concrete structures and infrastructure leads to an increase in computational cost of high-dimensional MC simulations, if effects of spatial or temporal variability is to be considered. However, reduction schemes proposed or refereed in this paper suggests that such task is feasible not only for simple analytical examples, but also for comprehensive FEM models of complex structural systems.

8 ACKNOWLEDGEMENT

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