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Stochastic Fracture Mechanics and Size Effect

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STOCHASTIC FRACTURE MECHANICS AND SIZE EFFECT

STOCHASTICKÁ LOMOVÁ MECHANIKA A VLIV VELIKOSTI KONSTRUKCÍ

Short version of Ph.D. Thesis

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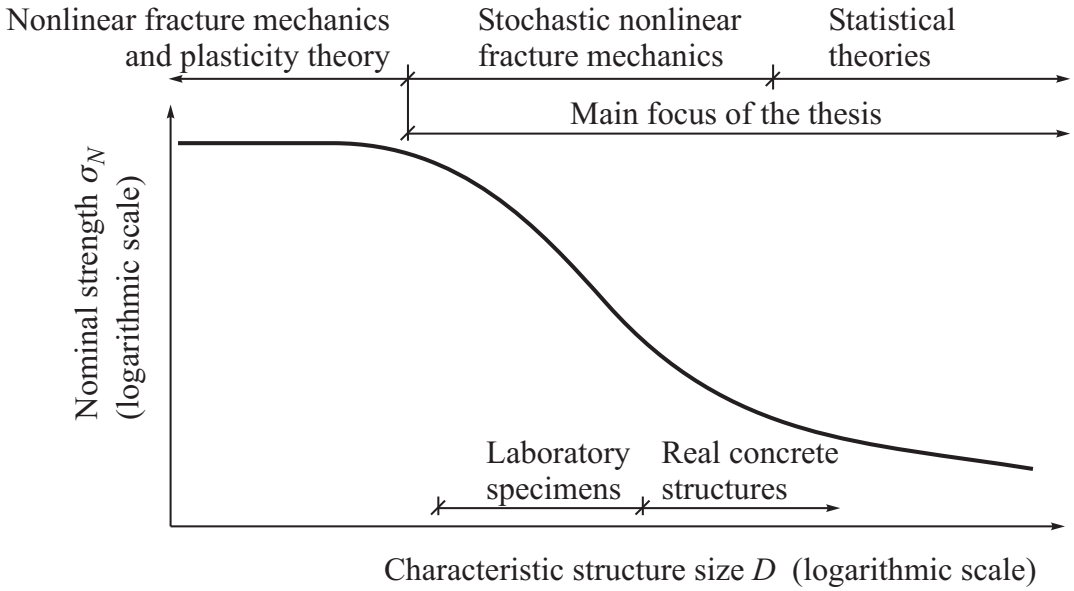
OBSAH

1 STATE OF THE ART

The salient feature of quasi-brittle materials is a complex size effect on structural strength. Size effect phenomenon manifests itself in form of a strong dependence of a nominal strength (nominal stress at the failure load) on a characteristic dimension (size) of the geometrically similar structures, see Fig. 1. Since the uncertainties and spatial variability is inherently present in nature, the nominal strength has certain variability. The size effect is also characterized/accompanied by the change of the nominal strength variability for different structure sizes. Size effect phenomenon has a great impact on a safe design and assessment of structures. The size effect is not present in current strength theories (either plasticity or elasticity). The problem is that real large structures usually fracture under smaller failure load than laboratory size specimens, see Fig. 1.



Obr. 1: Illustration of size effect on nominal strength and the range of structural sizes of interest in the thesis

The history of description of size effect can be seen as a history of two fundamentally different approaches – deterministic and statistical explanations. The first explanation was definitely statistical and dates back to the pioneering work of [1] and many others, mainly mathematicians. Phenomenon that larger specimens will usually fracture under relatively smaller applied load was associated with the statistical theory of extreme values at that time. Then most re-searchers focused on the energetic basis of size effect and the main achievements were purely deterministic. Let us mention e.g. the book of [2] as an extensive source of information. Researchers used different theories, from early works e.g. [3, 4, 5] considered uncertainties involved in concrete fracture. Some authors attempt to explain size effect by theories of fractals [6] . Recently, there are attempts to combine last decade's achievements of both fracture mechanics and reliability engineering e.g. [7, 8, 9, 10] and others. Arguments coming from the state of the art represent basis for the need to

combine efficient reliability techniques with present knowledge in the field of nonlinear fracture mechanics. Remarkable development of computer hardware makes the numerical simulation of Monte Carlo type of complex nonlinear responses possible. The reasons for complex reliability treatment of nonlinear fracture mechanics problems can be summarized as follows: (i) *Modeling of uncertainties* (material, load and environments) in classical statistical sense as random variables or random processes (fields). The possibility to use statistical information from real measurements; (ii) *Inconsistency of design* to achieve safety using partial safety factors – fundamental problem; (iii) *Size effect phenomena*.

2 AIMS AND STRUCTURE OF THE THESIS

The title of the thesis "Stochastic fracture mechanics and size effect" suggests the attempt to combine both, the advanced tools of fracture (nonlinear) mechanics and stochastic approaches in order to model the complex behavior of real material/structures considering material randomness or variability. The whole focus looks towards complex description and understanding of size effect phenomena. The main attention is devoted to concrete as a main representative of quasibrittle material (such as rock, tough ceramics, snow and ice, etc.) and one of the most important building materials in civil engineering. This thesis is focused mainly on the range of sizes where both phenomena, statistical and deterministic plays a significant role, see the transitional zone in Fig. 1. This transition represents the range with the most difficult structural scaling theory.

Aims of chapter 3 are to briefly review simulation methods of Monte Carlo type for efficient structural stochastic assessment and to introduce Latin Hypercube Sampling (LHS) as a technique suitable for an analysis of computationally intensive problems which is typical for a nonlinear FEM analysis. In particular the chapter suggests a new procedure for efficient imposition of statistical correlation among input variables. The technique is robust, efficient and very fast.

The following chapter 4 is devoted to efficient simulation of random fields for problems of stochastic continuum mechanics. In particular, the transformation of the original random variables into a set of uncorrelated random variables is presented using an eigenvalue orthogonalization procedure. It is demonstrated that only a few of these uncorrelated variables with largest eigenvalues are sufficient for the accurate representation of the random field. The error induced by such truncation will be an object of study in this chapter as well. An error assessment procedure for simulated samples of random fields is proposed. We show that a clear indication of the errors in autocorrelation structure is the fulfillment of norms used as objective functions in algorithm proposed in the preceding chapter.

The next chapter of the thesis is focused on *textile reinforced concrete*, a new composite material for special purposes. The thesis presents a newly developed micromechanical model which is combined with advances stochastic techniques (ran-

dom variables and random processes capturing the spatial variability of uncertain parameters). These models are given to context with classical approaches and we proved that there must exist (as opposite to Weibull integral) statistical length scale. It is explained why the nonlocal Weibull integral [11, 10, 12] is not general enough solution for the presented problems. We propose new formulas which are designed based on asymptotic matching for approximation and prediction of the yarn strength under various conditions and for the whole range of yarn lengths. These formulas are compared to available statistical theories of strength of bundles. The detailed analysis of all substantial effect in the context of tensile test of yarn enabled design of practical procedure of testing and evaluation of yarn strength. It is shown how to decompose, analyze and compose partial phenomena present in the yarn tensile test.

The following chapter introduces a new approach to stochastic nonlinear analyzes of large structures. Standing firmly on the *statistical theory of extreme values* the text proposes a practical tool for simulation of random scatter (spatial variability) in the context of FEM which is independent of the mesh. In some sense the approach brings similar features to famous *crack band* model in deterministic computational fracture mechanics [13]. Similarly to the crack band model which is proved to be theoretically correct and compared to cohesive (fictitious) crack model, the developed *stochastic crack band model* is derived from elaborate theory of ordered statistics and extreme values [14, 15, 16, 1, 17]. The range of applicability (large structures) is explained and it is shown that the model performs well in the size regions, where the combination of NLFEM and simulation of random fields is not useful. This is because in case of large structures the computational demands render the utilization of random fields inapplicable. The feasibility, correctness and predictive power of the approach is shown using numerical examples.

The problem of *structural scaling* in a broad range of sizes is studied in chapter 6. The behavior of general quasibrittle material is shown to be the complex case of behavior covering both the plastic and elastic-brittle behavior on two asymptotic extremes of sizes. The work resulted in the *new combined size effect formula for crack initiation problems of quasibrittle failure*. The new law covers both the deterministic scaling (characteristic material length) and statistical scaling (autocorrelation length of variable strength) and their interaction over the whole range of sizes. The asymptotic limits are checked with help of deterministic plasticity of the small-size structures and stochastic-brittle behavior (Weibull type) of the large-size structures. A numerical verification of the theoretical consistency with the assumptions is performed with the practical example of Malpasset Dam failure in French Alps [18].

The computational tools used for numerical modeling were not ready at the beginning of author's doctoral study. In particular the stochastic simulations were done with simulation software developed by the author. The software constitutes the core of computer program FREET presented in chapter 7.

3 SIMULATION OF RANDOM VARIABLES

3.1 Introduction

The aim of statistical and reliability analysis of any computational problem which can be numerically simulated is mainly the estimation of statistical parameters of response variable and/or theoretical failure probability. Pure Monte Carlo simulation cannot be applied for time-consuming problems, as it requires large number of simulations (repetitive calculation of response). Small number of simulations can be used for acceptable accuracy of statistical characteristics of response using stratified sampling technique Latin Hypercube Sampling [19, 20, 21]. Briefly, it is a special type of Monte Carlo numerical simulation which uses the stratification of the theoretical probability distribution functions of input random variables. Stratification with proportional allocation never increases variance compared to IID sampling, and can reduce it. The efficiency of LHS technique was showed first time in work of [19], but only for uncorrelated random variables. A first technique for generation of correlated random variables has been proposed by [22]. One approach has been to find Latin hypercube samples in which the input variables have small correlations. Authors of [22] perturbed Latin hypercube samples in a way that reduces off diagonal correlation – they diminished an undesired random correlation. The technique is based on iterative updating of sampling matrix, Cholesky decomposition of covariance/correlation of matrix $\boldsymbol{Y}$ has to be applied. In their method, as a measure of the statistical correlation, the Spearman correlation coefficient is used. The estimated correlation matrix S is symmetric, positive definite (unless some rows have an identical ordering). Therefore the Cholesky decomposition of the matrix $\boldsymbol{S}$ may be performed. The technique can be applied iteratively and it can result in a very low correlation coefficient if generating uncorrelated random variables.

3.2 LHS: Sampling and statistical correlation

In the context of numerical simulation methods for structural reliability theory, LHS is based on Monte Carlo type of simulations of vector $\boldsymbol{Y}$ under prescribed probability distributions. Realizations are simulated in a special way: the range of probability distribution function $f_i(Y_i)$ of each random variable Y_i is divided into N_{Sim} equidistant (equiprobable) intervals, where N_{Sim} is the number of simulations planned (number of samples for each random variable). The identical probability $1/N_{Sim}$ for layers on distribution function is usually used. The representants of the equiprobable intervals are selected randomly; realizations are then obtained by inverse transformation of distribution function. The selection of midpoints as representants of each layer is the most often used strategy:

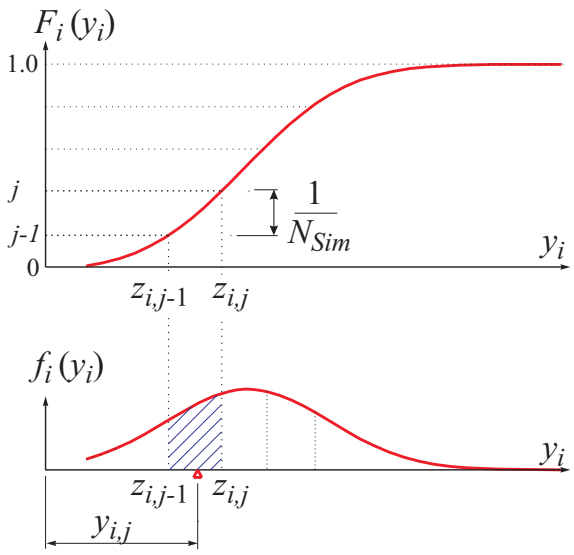
$$y_{i,j} = F_i^{-1}\left(v_{i,j}\right) = F_i^{-1}\left(\left(j - 0.5\right)/N_{Sim}\right) \ , \quad j = 1, \ldots, N_{Sim} \tag{1}$$

where $y_{i,j}$ is the j-th sample of i-th random variable Y_i ($i = 1, \ldots, N_V$), F_i^{-1} is the inverse of cumulative distribution function of this random variable. It could be challenged to this simple methodology. One can criticize reduction of samples selection to the midpoints in intervals (we call it interval *median*). Such objection deals mainly with the tails of PDF, which mostly influences variance, skewness and kurtosis of sample set. This elementary simple approach was already overcome by sampling of mean values related to intervals, e.g. [23]:

$$y_{i,j} = N_{Sim} \int_{z_{i,j-1}}^{z_{i,j}} y \cdot f_i(y)\,\mathrm{d}y \tag{2}$$

where f_i is the probability density function of variable X_i and the integration limits are: $z_{i,j} = F_i^{-1}(j/N_{Sim})$.

Samples then represent each one-dimensional marginal PDF better in terms of distance of point estimators from the exact statistics. In particular, the mean value is achieved exactly (analytical expression preserves the mean) and estimated variance of data is much closer to the original one. For some PDFs (including Gaussian, Exponential, Laplace, Rayleigh, Logistic, Pareto, or others) the integral (2) can be solved analytically. In case of no or difficult solution of primitive it is necessary to use an additional effort: numerical solution of the integral. However, such increase of computational effort is worthwhile indeed.



Obr. 2: Samples as the probabilistic means of intervals

Samples selected by both described ways are almost identical close excluding those in the tails of PDFs. Therefore more difficult method could be used there only considering the fact that tail samples mostly influence estimated variance of sample set. Generally in both cases, regularity of sampling (the range of distribution function is stratified) ensures good sampling and consequently good estimation of statistical parameters of response using small number of simulations.

Having the samples of each marginal random variable ready, we may proceed to the second step of LHS: statistical correlation imposition. There are generally two problems related to LHS concerning statistical correlation: First, during sampling an undesired correlation can be introduced between random variables. For example instead a correlation coefficient zero for uncorrelated random variables undesired correlation, e.g. 0.6 can be generated by random. It can happen especially in case of very small number of simulations (tens), where the number of interval combination

is rather limited. Second problem we face is: how to introduce prescribed statistical correlation between random variables defined by the target correlation matrix $\boldsymbol{K}$. Since the currently known techniques for imposition of statistical correlation in to the table of samples of random vector have some severe restrictions, we have developed a new scheme based on simulated annealing optimization algorithm.

3.3 Stochastic optimization method Simulated Annealing

The imposition of prescribed correlation matrix into sampling scheme can be understood as an optimization problem: The difference between the prescribed $\boldsymbol{K}$ and estimated (generated) $\boldsymbol{S}$ correlation matrices should be as small as possible. A suitable measure of the distance between $\boldsymbol{K}$ and $\boldsymbol{S}$ matrices can be introduced; a possible norm is the maximal difference of correlation coefficients between matrices:

$$E_{\max} = \max_{1 \le i \le j \le N_V} w_{i,j} \left| S_{i,j} - K_{i,j} \right| \tag{3}$$

or a norm E which takes into account deviations of all correlation coefficients can be more suitable:

$$E_{\text{overal}} = \sqrt{\sum_{i=1}^{N_V - 1} \sum_{j=i+1}^{N_V} w_{i,j} \left(S_{i,j} - K_{i,j} \right)^2} \Big/ \sum_{i=1}^{N_V - 1} \sum_{j=i+1}^{N_V} \sqrt{w_{i,j}} \tag{4}$$

This norm is normalized with respect to the number of considered correlation coefficients (entries of lower triangle in the correlation matrix). The corresponding weights $w_{i,j}$ are included because in real applications it can be a greater confidence to one correlation coefficient (good data) and a smaller confidence to another one (just estimation).

The norm E has to be minimized, from the point of view of definition of optimization problem, the *objective function* is and the *design variables* are related to *ordering* in sampling scheme

It is well known that deterministic optimization techniques and simple stochastic optimization approaches can very often fail to find the global minimum [24, 25]. They are generally strongly dependent on starting point (in our case the initial configuration of sampling scheme). Such techniques fail and finish with some local minimum such that there is no chance to escape from it. In our problem we are definitely facing the problem with multiple local minima. Therefore we need to use the stochastic optimization method which works with nonzero probability of escaping from local minima. The simplest form is the two-membered evolution strategy which works in two steps: **mutation** and **selection**.

Step 1 (mutation): In the r-th generation a new arrangement of random permutations matrix used in LHS is obtained using random changes of ranks, one change is applied for one random variable. Generation should be performed randomly. The

objective function (norm E) can be then calculated using newly obtained correlation matrix (it is called "offspring norm" and the norm E calculated using former arrangement is called "parent norm").

Step 2 (selection): The selection chooses the best norm between the "parent" and "offspring" to survive: For the new generation (permutation table arrangement) the best individual (table arrangement) has to give a value of objective function (norm E) smaller than before.

Such an approach has been intensively tested using numerous examples. It was observed that the method in most cases could not capture the global minimum. It failed in a local minimum and there was no chance to escape from it, as only the improvement of the norm resulted in acceptance of "offspring". More efficient technique had to be applied. The step "Selection" can be improved by Simulated Annealing approach, a technique which is very robust concerning the starting point (initial arrangement of random permutations table). The Simulated Annealing is optimization algorithm based on randomization techniques and incorporates aspects of iterative improvement algorithms. The difference compared to simple approach described above is that there is a chance to accept offspring leading to a worse norm and such chance is based on the Boltzmann probability distribution using the difference between the norms E before and after random change (parent and offspring norm). There are two possible branches to proceed in the step 2 (selection):

1. New arrangement (offspring) results in decrease of the norm E. Naturally "offspring" is accepted for the new generation.
2. New arrangement does not decrease the norm E. Such "offspring" is accepted with the probability given above (which changes as the temperature T changes). As a result there is much higher probability that the global minimum is found in comparison with deterministic methods and simple evolution strategies.

Constant k_b relates E and T; however, it can be considered to be equal to one in our case because both quantities share the same units of correlation measure. Fortunately, our problem is constrained in the sense that all possible elements of correlation matrix are always within the interval $\langle -1; 1 \rangle$. Based on this fact the maximum of the norm E can be estimated using prescribed and hypothetically "most remote" matrices $\boldsymbol{K}$ from $\boldsymbol{S}$, so the initial setting of parameters can be performed without the guess of the user and the "trial and error" procedure.

The initial temperature has to be decreased step by step, e.g. using reduction factor after constant number of iterations (e.g. thousands) applied at current temperature $T_{i+1} = T_i \cdot 0.95$. Note that more sophisticated cooling schedules are known in Simulated Annealing theory [24, 25]. As the number of simulations increases, the estimated correlation matrix is closer to the target one. Figure 8 shows the decrease of norm during SA-process. Such figure is typical and should be monitored.

4 SIMULATION OF RANDOM FIELDS

4.1 Introduction

Stochastic finite element method (SFEM) had facilitated the use of random fields in computational mechanics. Many material and other parameters are uncertain in nature and/or exhibit random spatial variability. Efficient simulation of random fields for problems of stochastic continuum mechanics is in the focus of both researchers and engineers. Achievements in stochastic finite element approaches increased the need for accurate representation and simulation of random fields to model spatially distributed uncertain parameters.

The spatial variability of mechanical and geometrical properties of a system and intensity of load can be conveniently represented by means of random fields. Because of the discrete nature of the finite element formulation, the random field must also be discretized into random variables. This process is commonly known as random field discretization. Various methods have been developed for the representation and simulation of random fields utilized within the framework of SFEM [26, 27]. In following we will deal with random fields simulation based on *orthogonal transformation of covariance matrix* in connection with different types of Monte Carlo simulation. These methods produce stationary and ergodic Gaussian processes. We will focus on error assessment of simulated fields and utilization of LHS methodology thoroughly discussed in the preceding chapter.

Since the computational effort in reliability problem is proportional to the number of random variables it is desirable to use small number of random variables to represent a random field. Simulation of the random field by a few random variables is especially suitable for problems where theoretical failure probability should be calculated. To achieve this goal, the transformation of the original random variables into a set of uncorrelated random variables can be performed through an eigenvalue orthogonalization procedure [27]. It is demonstrated that a few of these uncorrelated variables with largest eigenvalues are sufficient for the accurate representation of the random field. The error induced by such truncation will be an object of study in this chapter as well.

4.2 Orthogonal transformation of covariance matrix

Suppose that a spatial variability of random parameter is described by the Gaussian random field $a(\boldsymbol{x})$, $\boldsymbol{x} = (x, y, z)$ is the vector coordinate which determines the position on the structure. A continuous field $a(\boldsymbol{x})$ is described by discrete values $a(\boldsymbol{x}_i) = a(x_i, y_i, z_i)$, where $i = 1, \ldots, N$ denotes the discretization point.

As the randomness of the spatial variability in 3-$dimensional$ nature is generally not isotropic, the autocorrelation function of the spatial homogeneous random field is supposed to be a function of the distances between two points $|\Delta x|$, $|\Delta y|$

and $|\Delta z|$. The following commonly used exponential form of an autocorrelation function is considered:

$$R_{aa}(\Delta x, \Delta y, \Delta z) = \exp\left[-\left(\frac{|\Delta \mathrm{x}|}{\mathrm{d_x}}\right)^{\mathrm{pow}} - \left(\frac{|\Delta \mathrm{y}|}{\mathrm{d_y}}\right)^{\mathrm{pow}} - \left(\frac{|\Delta \mathrm{z}|}{\mathrm{d_z}}\right)^{\mathrm{pow}}\right] \quad (5)$$

in which d_x, d_y and d_z are positive parameters called *correlation lengths*. With increasing d a stronger statistical correlation of a parameter in space is imposed and opposite.

The random variables needed for discrete representation of random field in discretization points can be transformed to the uncorrelated normal form by solution of an eigenvalue problem [27]. In order to reduce the computational effort, an eigenvalue orthogonalization procedure can be employed: $\mathbf{C_{XX}} = \mathbf{\Phi \Lambda \Phi}^T$, where $\mathbf{C_{XX}}$ is the covariance matrix. The matrix $\mathbf{\Phi}$ represents the orthogonal transformation matrix (eigenvectors). The covariance matrix in the uncorrelated space $\boldsymbol{Y}$ is the diagonal matrix $\mathbf{\Lambda} = \boldsymbol{C_{YY}}$, where the elements of diagonal are the eigenvalues $(\lambda_1, \lambda_2, \ldots, \lambda_N)$ of covariance matrix $\boldsymbol{C_{XX}}$.

Usually, not all eigenvalues have to be calculated and considered for next step (simulation) as the fluctuations can be described almost completely by a few random variables. This can be done by arranging the eigenvalues in descending order, calculating the sum of the eigenvalues up to the i-th eigenvalue and dividing it by trace of $\mathbf{\Lambda}$. The reduction of number of random variables in fact depends on relationships between total dimensions and discretization of the structure (model) and given correlation lengths.

Let the chosen number of important dominating random variables by eigenvalue analysis be N_V. Now, the eigenvector matrix $\mathbf{\Phi}$ denotes the reduced eigenvector matrix containing only the respective eigenvectors to the N_V most important eigenvalues. Then the vector of uncorrelated Gaussian random variables $\boldsymbol{Y}^T = [Y_1, Y_2, \ldots, Y_{N_V}]$ can be simulated by a traditional way (Monte Carlo simulation). The random variables of vector $\boldsymbol{Y}$ have mean zero and standard deviation $\sqrt{\lambda_1}, \sqrt{\lambda_2}, \ldots, \sqrt{\lambda_{N_V}}$. The transformation back into correlated space yields the random vector $\boldsymbol{X}$ (random field) by the relation:

$$\boldsymbol{X} = \mathbf{\Phi} \boldsymbol{Y} \quad (6)$$

Latin Hypercube Sampling utilization

An increased efficiency of the approach using reduced set of dominant variables can be gained by usage of variance-reduction techniques (such as LHS) for simulation of uncorrelated random variables [28]. We will show some further improvements and detailed error assessment of such combined approach. A comparison with classical Monte Carlo simulation (MCS) reveals the superior efficiency and accuracy of the method. The key point is that matrix $\boldsymbol{Y}$ of random variables from the uncorrelated space is assembled with utilization of stratified sampling LHS. It is expected that the superiority of this stratified technique comparing MCS will continue also for accurate representation of random field, thus leading to a decrease

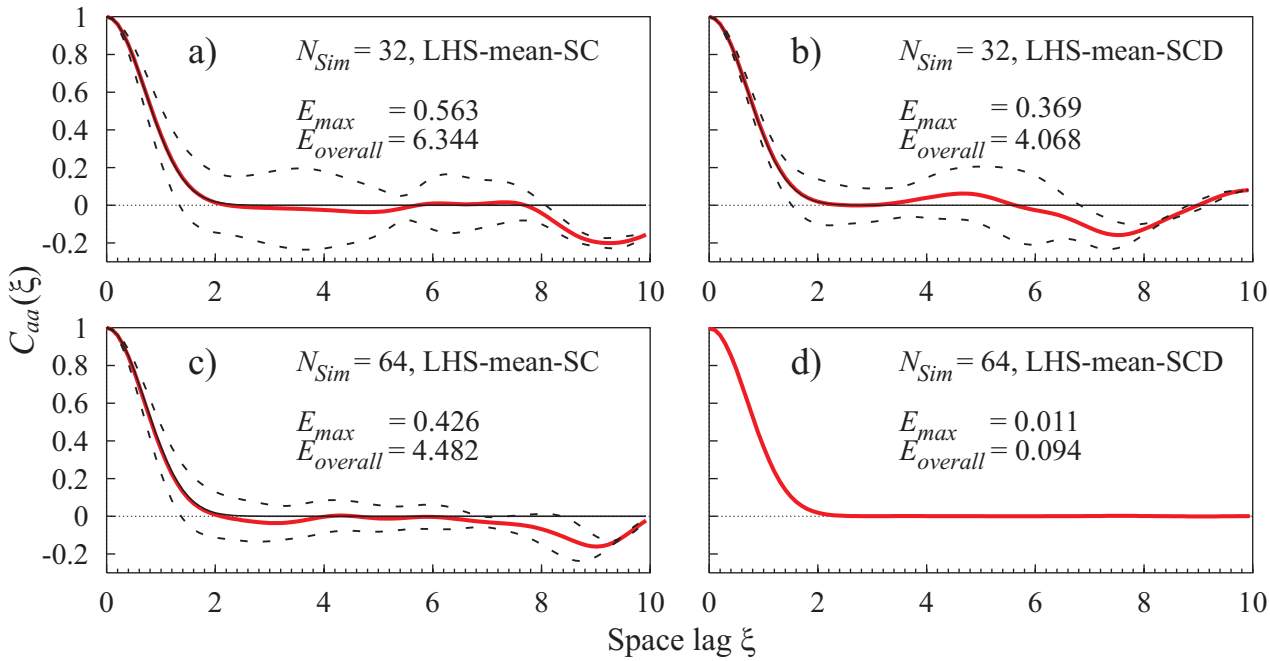
of number of simulations needed. This should be proved at least numerically. The methodology for an assessment of error of simulations is described in the next section.

4.3 Error assessment of random field simulation

When any method for random field simulation is used it is required that the statistical characteristics of the field generated be as close as possible to the target parameters. Generally, the mean values, variances, correlation and spectral characteristics (statistics) cannot be generated with absolute accuracy. Basic information about random field is captured by its second moment characteristics, i.e. the mean function and the covariance function. Some samples of random fields for a parameter are simulated from the population parameters. A certain statistic of the particular simulation may be very close to or quite far away from the value of corresponding target parameter. When the seed of the pseudo-random number generator is changed other random fields are generated and other values of all sample statistics are naturally obtained. Therefore, each of these statistics can be considered as a *random variable* with some mean value and variance. The simulation technique is considered as best one which gives an estimated mean value of the statistics very close to the target mean value and also closest to zero variance of the statistics. In our case of zero mean value and unit variance of random field (basic target statistical parameters) we expect to get estimated mean around zero and variance around one.

Reduction of spurious correlation

What are the consequences of spurious correlation to autocorrelation function variability of simulated random fields? The study has been done for correlation length 1 m and for two numbers of simulations - an error assessment based on samples simulations from population is described later. The results are shown in Fig. 3, mean values and the scatterband represented by mean $\pm$ standard deviation of autocorrelation function is plotted. Figure 3a) shows the result for 32 simulations, spurious correlation is not diminished (LHS-mean-SC). It is obvious that capturing of target autocorrelation function is weak and the scatterband is large. The explanation is clear, using only 32 simulations leads to large both norms E_{max} and $E_{overall}$. When N_{Sim} increases to 64, capturing of autocorrelation function is better, Fig. 3c), d). Note that now the alternative with diminished spurious correlation by SA resulted in excellent function capturing with very small variability, see figure 3d). This fact corresponds with both norms which are in case d) very small. It can be seen that the spurious correlation at the level of simulation of independent random variables influences negatively the autocorrelation function. These illustrative indicate that norms used as objective functions in Simulated Annealing algorithm can be interpreted as a qualitative prediction of resulting quality of autocorrelation structure.



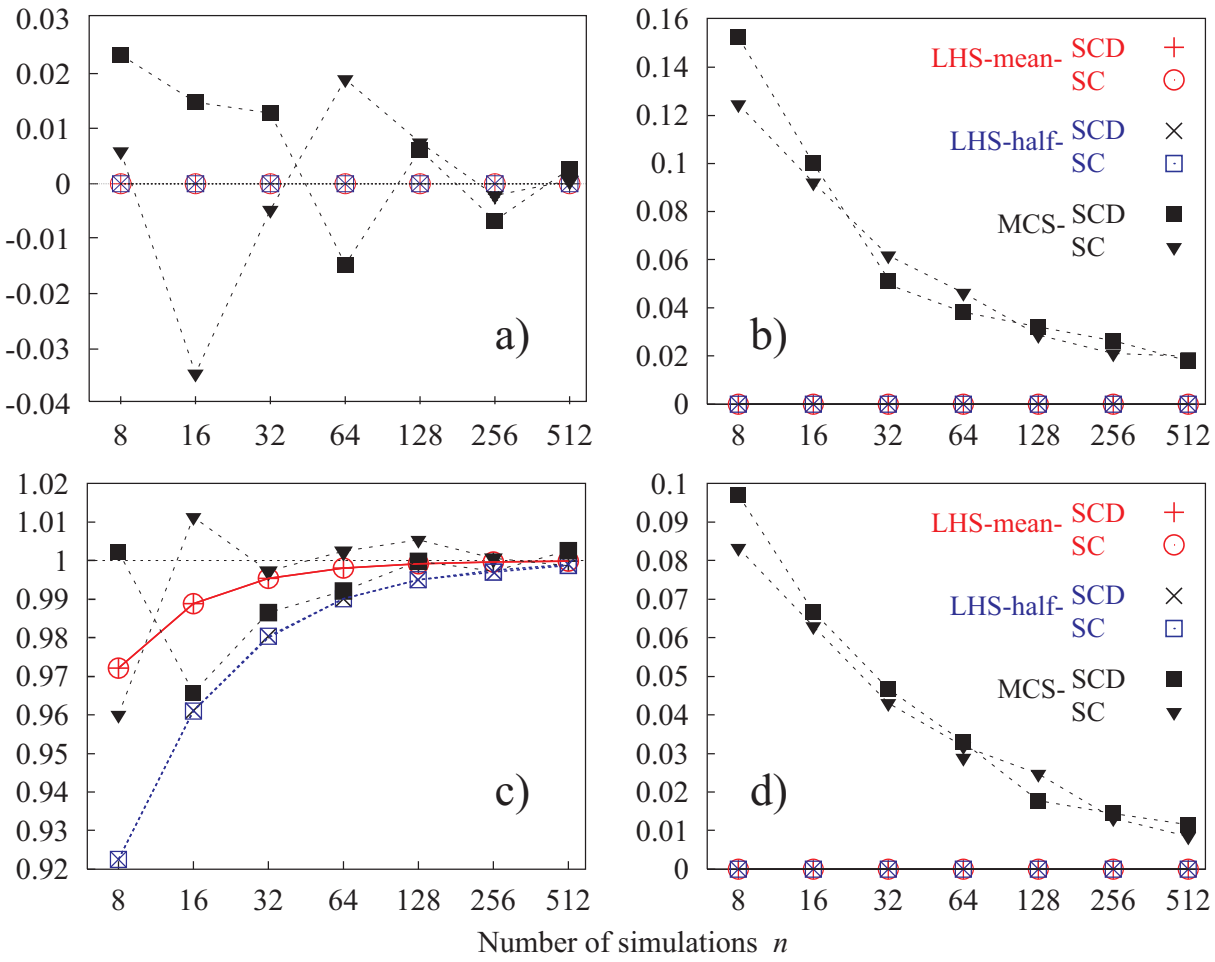
Obr. 3: Scatterband of autocorrelation function $C_{aa}(\xi)$ for $N_{Sim} = 32$: a) LHS-mean-SC; b) LHS-mean-SCD; and $N_{Sim} = 64$: c) LHS-mean-SC; d) LHS-mean-SCD

Classification of sampling schemes

When any method for random field simulation is used, it is required that the statistical characteristics of the field generated should be as close as possible to the target statistical parameters. Generally, the mean values, standard deviations, correlation and spectral characteristics (we will use the common term "statistics") cannot be generated with absolute accuracy. All possibilities of sampling method can be summarized as follows: (i) crude Monte Carlo simulation (MCS); (ii) Latin hypercube sampling under original scheme, [19] , (LHS-median); (iii) Latin hypercube sampling under improved scheme, [23] (LHS-mean). These schemes can be applied in two alternatives: (1) No attention is paid to spurious correlation (SC); (2) Spurious correlation diminished (SCD) There are 6 combinations, cases with SC and SCD, which are sampled by MC, LHS-half and LHS-mean. What is the best alternative? Naturally, the quality of sampling schemes can be intuitively predicted even without numerical experiment, e.g. combination (MCS) and (SC) should definitely belong to worst case and combination of (LHS-mean) and (SCD) should be the most efficient.

The assessment can be done by performing more runs of the same simulation process with a different random setting of the seed of pseudo random number generator. Thus samples are artificially generated from the population in this way. Let us consider 1D structure of length 10 m (e.g. beam), the structure is divided into 128 discretization points associated with finite elements ($N = 128$). The region of small number of simulations ($N_{Sim} = 8, 16, 32, 64, 128, 256, 512$) has been selected in parametric study - implicitly it was supposed that the superiority of LHS should

appear for small number simulations (tens, hundreds). Number of runs $N_{run} = 30$ was selected for estimation of statistics. So the random fields had to be simulated $N_{run} \times N_{Sim}$ times for a statistics of interest. The results are plotted in Fig. 4. **Mean value:** An ability to simulate *mean value* of random field is excellent in all alternatives of LHS (figures a) and b)), even for very low number of simulations. This ability is rather poor in case of MCS, mean value of *mean* fluctuates and standard deviation of *mean* is high in comparison to LHS. **Standard deviation:** The ability to simulate *standard deviation* of random field is documented in figures c) and d). Again, capturing of this statistics is "random" in case of MCS, standard deviation of *standard deviation* is high in comparison to LHS. LHS-half underestimates mean value of *standard deviation* (figure c)) for low number of simulations. The capability of improved sampling scheme LHS-mean is much better and convergence to target statistic (unit standard deviation) is faster. This is a general feature of LHS tested at the level of random variables. An important fact is documented: diminishing spurious correlation has small influence on these basic statistics of random field. Note, that if we construct statistics presented in Fig. 4 for different correlation length of the field, similar trends will be obtained.



Obr. 4: Statistics of mean *and* standard deviation *($d = 1$ m): a) mean of* mean*; b) standard deviation of* mean*; c) mean of* standard deviation*; d) standard deviation of* standard deviation

5 SIZE EFFECT OF MULTI-FILAMENT YARNS

The tensile failure of fiber-reinforced composites is generally dominated by failure of the fiber bundle. The matrix material, whether polymer, ceramic or metal, serves mainly to transfer the load among the fibers through the elasticity, or yielding, debonding with sliding friction between the fiber and matrix. The matrix can carry some load in a metal or polymer matrix composite but, after matrix cracking, carries almost zero load in ceramic matrix composites. The two factors controlling fiber failure are (i) the statistical fiber strength and (ii) the stress distribution along the fiber direction. The stress along a fiber depends on the applied stress, but also on precisely how stress is transferred from a broken fiber to the surrounding intact fibers and matrix environment. This stress transfer is governed by the elastic properties of the constituents and by the fiber/matrix interface, and is difficult to obtain in the presence of more than one broken fiber. There are two load sharing rules. One is "global load sharing", i.e. loads dropped due to fiber break(s) are shared equally among intact fibers. The other is "local load sharing", i.e. dropped loads are carried preferably by filaments surrounding the broken filaments.

The presented work is focused particularly on fiber bundles under global (equal) load sharing. In particular we are focusing on size (length) effect of multi-filament yarn under tensile strength test. The available statistical models of strength of bundles are reviewed. Deterministic micromechanical computational model capable of tracing the whole load-deflection curve has been developed and used for identification and study of sources of randomness affecting the evolution of the stiffness during the loading of yarns in tension. It has been shown that also the stiffness evolution in the early stages of loading influences the maximum tensile force in the bundle. The model serves as a basis for a complex stochastic analysis of the complex size effects including all mentioned effects employing the random field simulation technique. Such stochastic modeling framework has been used for derivation of new size effect laws for each of the considered sources of randomness separately.

In order to introduce the statistical length scale in the Weibull power law for the mean size effect, we modify the classical law by introducing the length-dependent function $f(l)$ with the filament length l in the following form

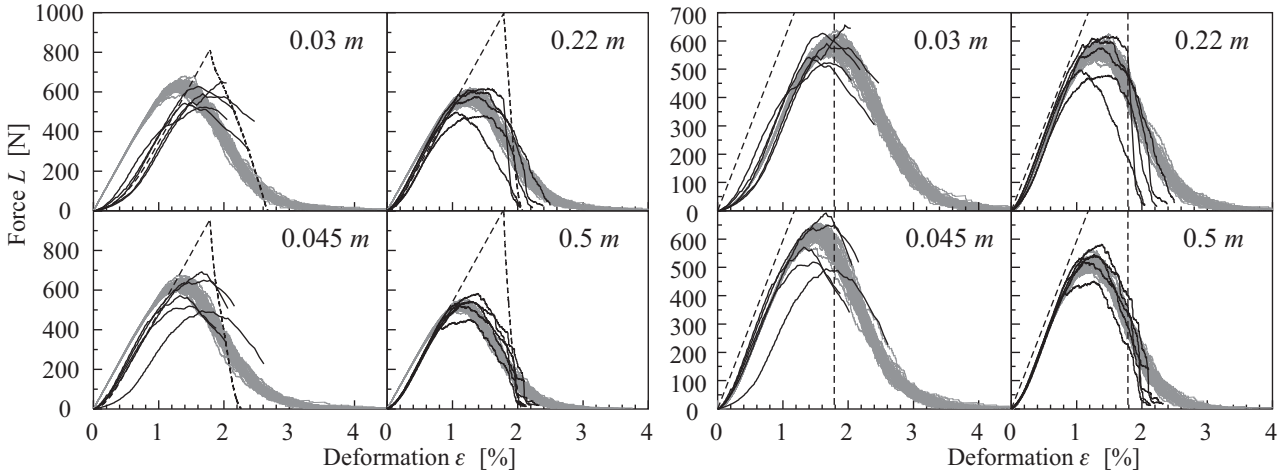
$$\sigma\left(l\right) = s_0 \left[-\ln\left(1 - P_f\right)\right]^{1/m} f(l) \tag{7}$$

where m is the Weibull modulus (shape parameter of Weibull strength distribution of fiber strength), s_0 is the scale parameter of strength distribution and P_f is the failure probability. We suggest to approximate the numerically obtained size effect on fibers with local tensile strength f^t described by random field by Eq. (7) with $f(l)$ expressed by one of the following formulas:

$$f\left(l\right) = \left(\frac{l}{l_\rho} + \frac{l_\rho}{l_\rho + l}\right)^{-1/m} \quad \text{or} \quad f\left(l\right) = \left(\frac{l_\rho}{l_\rho + l}\right)^{1/m} \tag{8}$$

This introduces the statistical length scale into (local) Weibull law in form of auto-correlation length l_ρ of random strength field.

Since the description of strength by random field still does not suffice to capture the size effects measured by real experiments, we have also studied and developed algorithm for back identification of *delayed activation* ε_0 of fibers. Shortly, if fibers between clamps do not have equal length, the longer ones activate in later stages of the test. If we identify also parameters of stiffness random field (Young's modulus of elasticity of elastic-brittle fibers E) we are able to simulate all essential features of real tensile test, see Fig. 5.



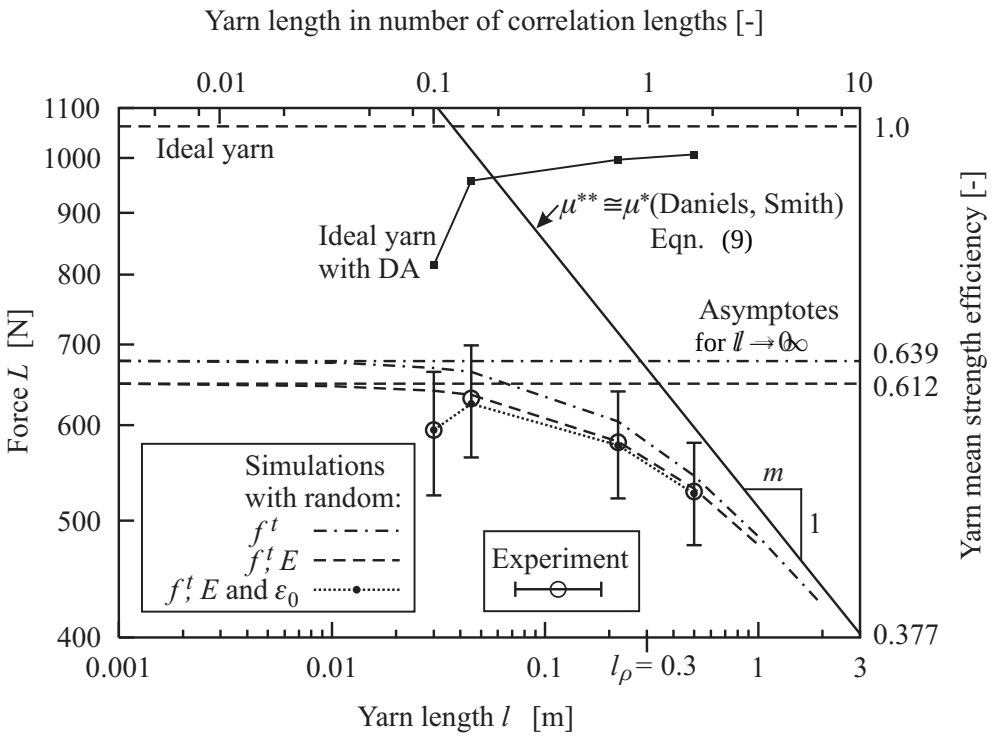
Obr. 5: Comparison of numerical simulations (gray) with experiments (black). Left: Simulations without delayed activation, randomized stiffness and strength. Diagram computed with DA plotted with dashed line. Right: Simulations with included delayed activation, randomized stiffness and strength. Diagrams computed with mean values plotted with dashed line.

The resulting size effect curve (double plot of length against strength of yarn) is plotted in Fig. 6.

In addition to the size effect curves obtained from the random process simulations Fig. 6 also shows the size effect obtained with the Daniels's [29] and Smith's [30] models calculated with $n_f = 1600$. Assuming that the filaments follow the Weibull scaling we may construct the bundle power law as a product of Daniels's prediction of the mean total strength [29] with the Weibull scaling $f(l) = (l_0/l)^{1/m}$

$$\mu^\star(l) = \mu^\star f(l) = \mu^\star \left(\frac{l_0}{l}\right)^{1/m} = s_0 \cdot m^{-1/m} \cdot \mathrm{e}^{-1/m} \left(\frac{l_0}{l}\right)^{1/m} . \tag{9}$$

Based on the lessons learned from the numerical analysis we have suggested approximation formulas describing the size effect laws due to the random strength or stiffness along the bundle. The obtained results have been verified with the help of the available analytical and numerical fiber bundle models by Smith and Daniels. However, the available fiber bundle models could not be used for modeling the response measured in the yarn tensile test, because they impose practically unachieveable assumptions of regular force transmission in the clamping and do not capture



Obr. 6: Size effect curves obtained numerically for the randomized f^t, ε_0, f_t together with E and all three parameters simultaneously.

the disorder in the structure of filaments in the bundle.

6 ENERGETIC-STATISTICAL SIZE EFFECT

6.1 Introduction and development of the new law

The size effect on nominal strength σ_N of concrete structures has basically two explanations, deterministic (energetic) and statistical (probabilistic). The former is caused by the stress redistribution on the fracture process zone, which is for different structure sizes about the same. The latter is explained by higher probability of low local strength for large structures.

Practical and simple approach to incorporate the statistical size effect into the design or the assessment of very large unreinforced concrete structures (such as arch dams, foundations and earth retaining structures, where the statistical size effect plays a significant role) is important. Failure load prediction can be done without simulation of Monte Carlo type utilizing the energetic-statistical size effect formula in mean sense together with deterministic results of FEM nonlinear fracture mechanics codes.

We propose a new improved law with two scaling lengths (deterministic and statistical) for combined energetic-probabilistic size effect on the nominal strength for structures failing by crack initiation from smooth surface. The role of these two lengths in the transition from energetic to statistical size effect of Weibull type is

clarified. Relations to the recently developed deterministic-energetic and energetic-statistical formulas are presented. We also clarify the role and interplay of two material lengths: deterministic and statistical.

The deterministic energetic size effect formula for crack initiation from smooth surface reads [31, 2, 32]:

$$\sigma_N(D) = f_r^{\infty}\left[1 + \frac{rD_b}{D + l_p}\right]^{1/r} \tag{10}$$

where σ_N is the nominal strength depending on the structural size D. Parameters f_r, D_b and r are positive constants representing the unknown empirical parameters to be determined. Parameter f_r represents solution of the elastic-brittle strength which is reached as a nominal strength for very large structural sizes. The exponent r (a constant) controls the curvature and the slope of the law. The exponent offers a degree of freedom while having no effect on the expansion in derivation of the law [31, 2]. Parameter D_b has the meaning of the thickness of cracked layer. Variation of the parameter Db moves the whole curve left or right; it represents the deterministic scaling parameter and is in principle related to grain size and drives the transition from elastic brittle ($D_b = 0$) to quasibrittle ($D_b > 0$) behavior.

By considering the fact that extremely small structures (smaller than D_b) must exhibit the plastic limit, a parameter l_p is introduced to control this convergence. The formula (1) represents the full size range transition from perfectly plastic behavior (when $D \to 0; D \ll l_p$) to elastic brittle behavior $(D \to \infty; D \gg D_b)$ through quasibrittle behavior. Parameter lp governs the transition to plasticity for small sizes D (crack band models or averaging in nonlocal models leads to horizontal asymptote). The case of $l_p \neq 0$ shows the plastic limit for vanishing size D and the cohesive crack and perfectly plastic material in the crack both predicts equivalent plastic behavior. For large sizes the influence of l_p decays fast and therefore the cases of $l_p \neq 0$ are asymptotically equivalent to case of $l_p = 0$ for large D.

The large-size asymptote of the deterministic energetic size effect formula (10) is horizontal: $\sigma_N(D)/f_r = 1$, see Fig. 7a). But this is not in agreement with the results of nonlocal Weibull theory as applied to modulus of rupture [12], in which the large-size asymptote in the logarithmic plot has the slope $-n/m$ corresponding to the power law of the classical Weibull statistical theory [1]. In view of this theoretical evidence, there is a need to superimpose the energetic and statistical theories. Such superimposition is important, for example, for analyzing the size effect in vertical bending fracture of arch dams, foundation plinths or retaining walls.

The statistical part of size effect and the existence of statistical length scale have been investigated in detail by the previous chapter for the particular case of glass fibers. By incorporating the result into the formula (10) we get a final law:

$$\sigma_N = f_r^{\infty}\left[\left(\frac{L_0}{L_0 + D}\right)^{r\,n/m} + \frac{rD_b}{l_p + D}\right]^{1/r} \tag{11}$$

This formula exhibits the following features:

- Small size left asymptote is correct (deterministic), parameter lp drives to fully plastic transition for small sizes.
- Large size asymptote is the Weibull power law (statistical size effect, a straight line with the slope -n/m in the double-logarithmic plot of size versus nominal strength)
- The formula introduces two scaling lengths: deterministic (D_b) and statistical (L_0). The mean size effect is partitioned into deterministic and statistical parts. Each have its own length scale, the interplay of both embodies behavior expected and justified by previous research. Parameter D_b drives the transition from elastic-brittle to quasibrittle and L_0 drives the transitional zone from constant property to local Weibull via strength random field. Note that the autocorrelation length l_ρ has direct connection to our statistical length L_0. This correspondence is explained in papers in the author's dissertation [18].

Having the summation in the denominators limit both the statistical and deterministic parts from growing to infinity for small D. So it remedies the problem that the previous energetic-statistical formulas [12] intersect the deterministic law at the size $D = D_b$ and therefore gives higher mean nominal strength prediction for small structures compared to the deterministic case. Note that for $m \to \infty$ it degenerates to deterministic formula (10). The same applies if $L_0 \to \infty$. The interplay of two scaling lengths using the ratio L_0/D_b is demonstrated in [18]. The question arises what is in reality the ratio L_0/D_b? Since both scaling lengths are in concrete probably driven mainly by grain sizes, we expect $L_0 \approx D_b$, so the simpler law with $L_0 = D_b$ should be an excellent performer for practical cases.

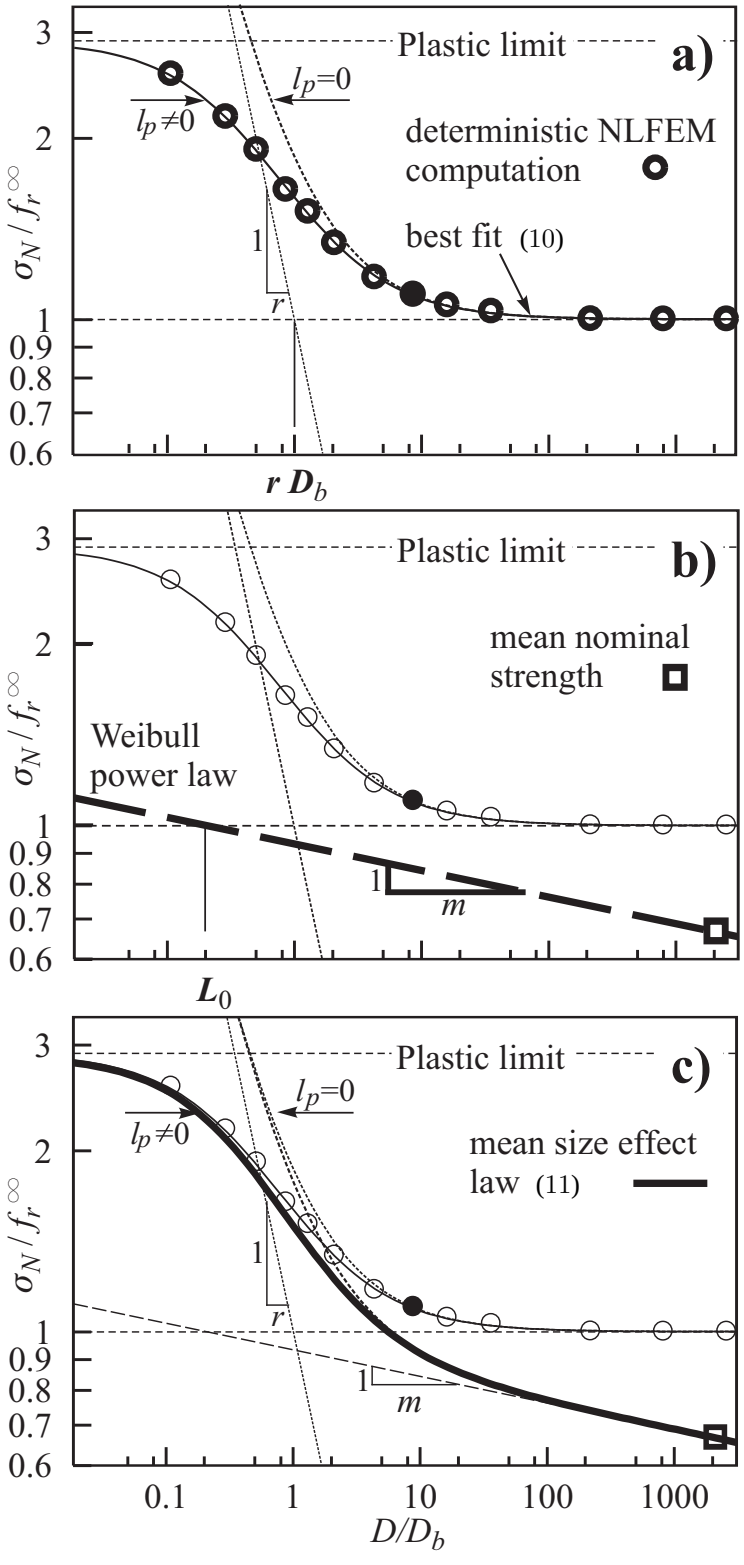
6.2 Superimposition of deterministic and statistical size effects

As was already mentioned deterministic modeling with NLFEM can capture only deterministic size effect. A procedure of superimposition with statistical part should be established. Such procedure of the improvement of the failure load (nominal stress at failure, deterministic size effect prediction) obtained by a nonlinear fracture mechanics computer code can be as follows:

1. Suppose that the modeled structure has characteristic dimension D_t. The natural first step is to create FEM computational model for this real size. At this level the computational model should be tuned and calibrated as much as possible (meshing, boundary conditions, material etc.). Note that we obtain a prediction of nominal strength of the structure (using failure load corresponding to the peak load of load-deflection diagram) for size D_t, but it reflects only deterministic-energetic features of fracture. Simply, the strength is usually overestimated at this (first) step, the overestimation is more significant as real

structure is larger. Result of this step is a point in the size effect plot presented by a filled circle in Fig. 7 a).

2. Scale down and up geometry of our computational model in order to obtain the set of similar structures with characteristic sizes $D_i, i = 1, \ldots, N$. Based on numerical experience a reasonable number is around 10 sizes and depends how the sizes cover transition phases. Therefore, sizes D_i should span over large region from very small to very large sizes. Then calculate nominal strength for each size $\sigma_{N,i}, i = 1, \ldots, N$. Note that for two very large sizes nominal strengths should be almost identical as this calculation follows energetic size effect with horizontal asymptote. If not, failure mechanism is not just only crack initiation, other phenomena (stress redistribution) plays more significant role and the procedure suggested here cannot be applied. The computational model has to be mesh-objective in order to obtain objective results (eg. crack band model, nonlocal damage continuum) for all sizes.
In order to ensure that phenomenon of stress redistribution (causing the size effect for the range of sizes) is correctly captured, well tested models are recommended for strength prediction. A special attention should be paid to the selection of constitutive law and localization limiter. The result of this step is a set of point (circles) in the size effect plot as shown in Fig. 7 a).



Obr. 7: Illustration of superimposition steps. a) Steps 1-4; b) Step 5 - determination L_0; c) Final formula

3. The next step is to obtain the optimum fit of the deterministic-energetic formula (10) using the set of N pairs $(\{D_i, \sigma_{N,i}\} : i = 1, \ldots, t, \ldots, N)$. Since the

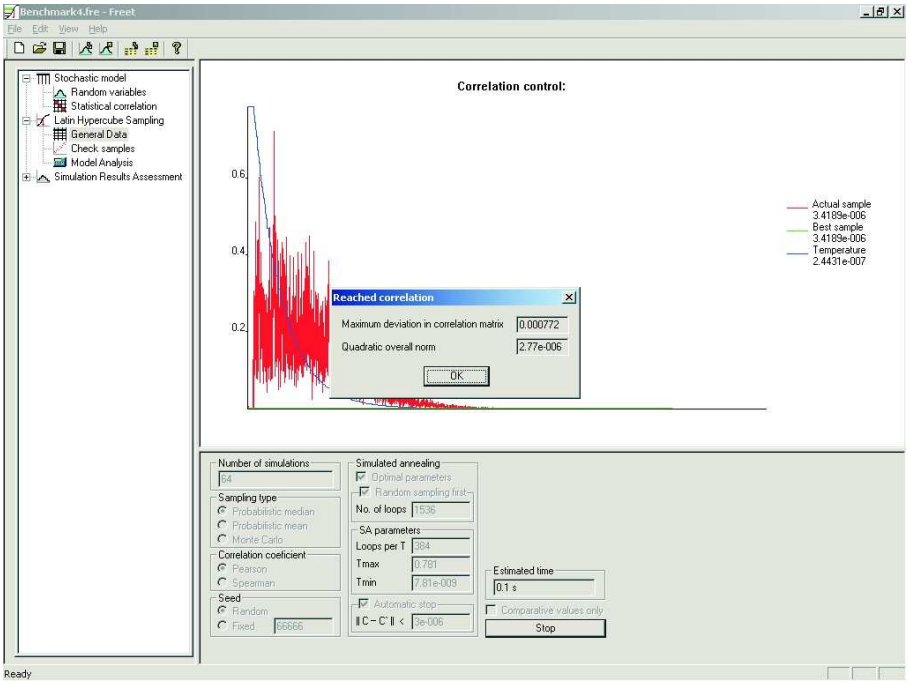
deterministic formula is generally nonlinear in fitted parameters (if $r \neq 1$ or $l_p \neq 0$) the algorithm for nonlinear regression fit is needed.

The parameter l_p can be excluded from the fit based on the plastic analysis [18]. Fit of the parameter f_r can also be avoided because this limit can be estimated from nonlinear FEM analysis as the value to which the nominal strength converges with increasing size. So we can be prescribe (for very large sizes), $\sigma_N/f_r = 1$ as asymptotic limit. The result of this step is illustrated by a fitted curve to the set of points in figure 7a).

4. There are three remaining parameters which should be substituted into statistical-energetic formula (11): n, m and L_0: Parameter n is the number of spatial dimensions (n = 1, 2 or 3). Parameter m represents the Weibull modulus of FPZ with Weibull distribution of random strength. Recent study [32] reveals that, for concrete and mortar, the asymptotic value of Weibull modulus $m \approx 24$ rather than 12, the value widely accepted so far. Ratio n/m therefore represents the slope of MSEC in size effect plot for $D \to \infty$. This means that for extreme sizes the nominal strength decreases, for two-dimensional (2D) similarity ($n = 2$), as the $-1/12$ power of the structure size. Note, that for different material the asymptotic value of Weibull modulus is different, eg. for laminates much higher than 24. Result of these 4 steps are shown for illustration in Fig. 7a). Parameter L_0 is now only remaining parameter to be determined. As it represents statistical length scale it seems to be that we will need to utilize a statistical software incorporated into your NLFEM code. But there is much simpler alternative based on simple calculation of local Weibull integral. Once the mean strength of a large structure is known (a square in the size effect plot, one can pass a straight line of slope $-n/m$ through the point (Weibull asymptote). Graphically, the intersection of the statistical asymptote with deterministic strength for infinite structure size (horizontal asymptote) f_r gives the statistical scaling length on D-axis L_0, see figure 1b), see [18].
5. As all parameters of statistical-energetic formula are determined, nominal strength can be calculated for any size. Using real size of the structure D_t the prediction of corresponding nominal strength $\sigma_{N,t}$ can be done using (11). This prediction will be generally different (lower) from initial deterministic prediction, Fig. 7c). The larger structure the larger difference is. The formula will provide us the strength prediction for the mean strength. Additionally, a scatter of strength can be determined just using the fundamental assumption of Weibull distribution. For the distribution we know two parameters, shape parameter m is prescribed initially, and scale parameters s can be calculated easily from predicted mean and Weibull modulus.

7 FREET SOFTWARE

A multi-purpose probabilistic software for statistical, sensitivity and reliability analyzes of engineering problems has been developed [33]. The software is based on efficient reliability techniques described above and the computational core is implemented by the author in C++ programming language. The GUI (graphical user interface) is being implemented by Dr. Rusina in C++. The software is designed in the form suitable for relatively easy assessment of any user-defined computational problem written in C++, FORTRAN or any other programming languages. The approach is general and can be applied for basic statistical analysis of computationally intensive problems. The basic aim of statistical analysis is to obtain the estimation of the structural response statistics (failure load, deflections, cracks, stresses, etc.). The FREET software integrated with the ATENA software were used to capture both the statistical and deterministic size effect obtained from experiments. Probabilistic treatment of nonlinear fracture mechanics in the sense of extreme value statistics has been recently applied for crack initiation problems which exhibits Weibull-type the statistical size effect [18].



Obr. 8: Imposing of statistical correlation

8 CONCLUSIONS

Simulation of random variables

In chapter 3 the new achievement is mainly the new efficient technique of imposing the statistical correlation based on Simulated Annealing. The technique is robust, efficient and very fast and has many advantages in comparison with former techniques. The increased efficiency of small-sample simulation technique LHS

can also be achieved by the proper selection of samples representing the layered probability content of random variables. The methods are implemented by author and constitutes the computation core of the multipurpose software package FREET for statistical, sensitivity and reliability analysis of computational problems. A future work is recommended in: (i) Implementation of advanced method for probabilistic analysis, in particular response surface, FORM and Importance Sampling; (ii) Further research in simulation of random vectors with prescribed simultaneous probability density function or just marginals and covariances.

Simulation of random fields

Chapter 4 confirms the superior efficiency of LHS and correlation control in the context of sample simulation of random fields. An attempt has been done to show better the role of correlation control - diminishing spurious correlation in random field simulation and importance of sampling schemes for simulation of uncorrelated random variables. It has been shown that a spurious correlation influences significantly the scatter of estimated autocorrelation function of simulated random fields. A clear indication of this scatter is the fulfillment of norms used as objective functions in Simulated Annealing algorithm to diminish spurious correlation at the level of underlying random variables. The quality of simulated samples of random fields should be assessed. An error assessment procedure has been proposed and performed for six alternatives of sampling schemes. Diminishing spurious correlation does not influence the capturing of these statistics but does influence significantly a realization of autocorrelation function of a random field. A future work is recommended in: (i) Study, development and implementation of simulation of non-Gaussian stochastic fields; (ii) The newly developed tools of stochastic computational mechanics in the form of stochastic finite element method (SFEM) will now enable complex numerical investigations. We expect both (i) verification of newly achieved theoretical results (e.g. in the form of the proposed size effect law for quasibrittle failure at crack initiation) and (ii) numerical computations of real examples focused on the influence of nonlinearities on failure probability estimations.

Size effect of multi-filament yarns

The performed stochastic simulations with the available experimental data revealed the existence of statistical length scale that could be captured by introducing an autocorrelation of random material properties. This represents the departure from the classical Weibull-based models that are lacking any kind of length-scale. The introduced model delivers a quasi-ductile response of the bundle from the ensemble of interacting linear-elastic brittle components with irregular properties. In this respect the present approach falls into the category of lattice models used to model quasi-brittle behavior of concrete. It should be noted, that due to the possibility to trace the failure process in a detailed way both in the experiment and in the simulation, the modeling of multi-filament yarns provides a unique opportunity to study the local effects in quasi-brittle materials. The possibility to generalize

the results for other quasi-brittle materials is worth further intensive studies; The obtained statistical material characteristics turned out to be of crucial importance for robust modeling of crack bridges occurring in the cementitious textile composites. The ”well designed” microstructure of the yarn and of the bond layer in the crack bridge may significantly increase the overall deformation capacity (ductility) of structural elements. The lessons learned from the present study will be applied in a more targeted development of new yarn and textile structures with an improved performance of crack bridges. Development of micromechanical model of bond behavior and its coupling with the developed models will be pursued next.

Energetic-statistical size effect

We have presented a broader theoretical treatment of connections between fiber bundle models and size effect of concrete structures. It has been shown how the statistical size effect at fracture initiation can be captured by a stochastic finite element code based on extreme value statistics, simulation of the random field of material properties and chain of bundles transition. The computer simulations of the statistical size effect in 1D based on stability postulate of extreme value distributions match the test data. However, in some cases the correct behavior cannot be achieved for other tests using a 1D treatment. A proper way of treating the stress redistribution is by the proposed macro-elements in 2D (or 3D), the scaling of which is based on the fiber bundle model capturing partial load-sharing and ductility in the finite element system. A simple and effective strategy for capturing the statistical size effect using stochastic finite element methods is developed which overcomes the problematic feature of stochastic finite element method: How to capture the statistical size effect for structures of very large sizes. The idea is to emulate the recursive stability property from which the Weibull extreme value distribution is derived. Usage of combination of a feasible type of Monte Carlo simulation and computational modeling of nonlinear fracture mechanics renders a probabilistic treatment of complex fracture mechanics problems possible. The approach may be understood as a computational trick based on extreme value theory similar to its counterpart in deterministic nonlinear analysis of fracture - crack band model. The interplay of deterministic and statistical lengths of quasibrittle structures has been clarified and the analytical formula for the nominal mean strength prediction of crack initiation problems has been derived and proposed. The law features two separate scaling lengths of structures governing two different sources of size effect: deterministic and statistical. The role of these two lengths in the transition from energetic to statistical size effect of Weibull type is explained. A practical procedure of superimposition of the deterministic and statistical size effects at crack initiation has been suggested. It requires only a few NLFEM analysis using scaled sizes so the necessity of time consuming statistical simulation is avoided. The prediction can be done without any special Monte Carlo simulation, which is usually used to deal with the influence of uncertainties on structural strength.

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Summary in Czech

Předložená práce shrnuje výsledky dosažené autorem během doktorského studia a které jsou podrobně rozvedeny v disertační práci autora. Nové přínosy lze spatřovat ve čtyřech oblastech: (1) simulace náhodných veličin a vektorů typu Monte Carlo se zaměřením na statistickou korelaci mezi veličinami; (2) simulace náhodných polí v kontextu stochastické metody konečných prvků a zaměření na posouzení přesnosti simulovaných vzorků s ohledem na různé metody použité při simulaci; (3) vývoj mikromechanického modelu zatěžování svazku vláken použitého jako výztuž do textilem vyztuženého betonu; zde se autor zaměřil na vliv délky svazku na pevnost ovlivněnou různými zdroji náhodnosti a prostorové proměnlivosti materiálových parametrů, byly navrženy procedury a vztahy pro podchycení těchto vlivů a (4) vlivem velikosti betonových konstrukcí na jejich únosnost; zde je představena nová metoda pro podchycení statistické složky vlivu velikosti podložená teorií extrémních hodnot a dále je sledován komplexní vliv velikosti (statistická i deterministická složka a jejich interakce). V poslední, čtvrté oblasti práce vedla k navržení a ověření nového vztahu pro komplexní vliv velikosti.

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Born on February 07, 1977 in Brno, Czech Republic
single, Czech nationality

Education

09/1995–06/2000 Master's degree "Ing." (equiv C-Eng or MSc) Brno University of Technology, Brno, Czech Republic Thesis: "On reliability calculations of problems of nonlinear continuum mechanics" (in Czech)

Awards, honors and scholarships

6/2000: Award of Dean, Brno University of Technology; 6/2000: Diploma thesis Award, Brno University of Technology; 6/2000: Award of Chancellor, Brno University of Technology; 01/2001: Doctoral scholarship, Hlávka foundation, Prague; 05/2001: Electricité de France, Conference Stipend of Excellence, FraMCoS, France, Paris, 2001; 04/2002: Award of Josef Hlávka foundation, Prague; 05/2002: Travel stipend for conference in Scotland, Dundee; 9/2002–6/2003: *Preciosa* scholarship; 09/2002: A good paper award at the 4^{th} International Ph.D. Symposium in Civil Engineering, Munich, Germany; 05/2003: M.I.T. Young Researcher Fellowship (award), 2^{nd} M.I.T. Conference, Boston, USA; 06/2003: *Cerra award*, ICASP 9 conference, San Francisco, USA 09/2003–03/2004: Fulbright Doctoral Fellowship, Northwestern University, Evanston, USA.

Specialization, research interests

Nonlinear fracture mechanics with focus on stochastic aspects. Size effects, scaling in structures. Efficient methods of reliability engineering, mathematical statistics (random variables, random fields and processes, extreme value theories) connected with nonlinear fracture mechanics methods (behavior of quasibrittle materials). Stochastic optimization techniques, structural safety and reliability, stochastic computational mechanics, random fields, Genetic algorithms, Monte Carlo simulation techniques, modeling of concrete structures mechanics, size effect of structures. Programming and software development.

Memberships, activities

since 09/2000 member of FRAMCOS society (**FRa**cture **M**echanics of **Co**ncrete **S**tructures)

since 01/2004 member of ASCE (American Society of Civil Engineers)

1997–1999 Academic senate and Branch convocation - section Structures and transportation constructions

09/2000 Member of Local Organizing Committee: Workshop *3RE*, Institute of Structural mechanics TUB together with Institute of Structural Mechanics, Weimar

02/2001 Chairman of section, Member of Local Organizing Committee: Brno University of Technology, Faculty of Civil Engineering, 3^{rd} Scientific PhD international workshop.

International cooperation

□ Prof. Z. P. Bažant Northwestern University, Evanston, Illinois, USA: stochastic fracture mechanics of quasibrittle materials

□ Dr. R. Chudoba, Technical University of Aachen (RWTH Aachen), Germany: stochastic fracture mechanics of textile reinforced concrete, computational mechanics

□ Dr. G. Cusatis, Technical University in Milano, Italy: micromechanical models of concrete (lattice and microplane modeling)

Teaching experience

09/2000–06/2004 Institute of Structural Mechanics, Faculty of Civil Engineering, Brno University of Technology, Brno, Czech Republic:
Elasticity & Plasticity; *Reliability of structures*; *Structural Analysis I*

Professional stays, visiting positions

4/2001 PhD course Elastic and Inelastic Analysis of Heterogeneous Materials. Certificate of Attendance from Czech university in Prague, Faculty of Civil Engineering, Department of Structural Mechanics

07/2001–08/2001 summer school (two-week course) Advanced Studies in Structural Engineering and CAE, 9^{th}European Summer Academy 2001. Certificate of Attendance from Bauhaus University Weimar, Germany, Civil & Structural Engineering. Passed final oral examination with the mark A (ECTS Grade) and therefore credited with 7 ETCS credits

08/2001–09/2001 Professional 6-week training IAESTE, Croatia, Zagreb. The Dalekovod Company. Focus on Antennae towers, transmission lines (steel structures); Foundations of structures (concrete structures and soil mechanics)

01/2003–03/2003 Visiting research position in Aachen, Germany. Invited lectures. Cooperation on development of methodology and software for consideration of stochastic aspects in failures of Textile Reinforced Concrete

04/2003–05/2003 Visiting research position in Aachen, Germany. Invited lectures. Cooperation on development of methodology and software for consideration of stochastic aspects in failures of Textile Reinforced Concrete

06/2003–07/2003 Visiting research position at Prof. Z.P. Bažant: Northwestern University, Evanston, IL, USA

08/2003 Fulbright preacademic training, University of Philadelphia, USA

8/2003–04/2004 Visiting research position (Fulbright scholarship) at Prof. Z.P. Bažant: Northwestern University, Evanston, IL, USA (extension supported by NSF grants to Prof. Z.P. Bažant)

Participation in Research projects

1997–2004	Theory, reliability and mechanism of damage statically and dynamically stressed structures. Project of the Czech Ministry of Education CEZ: J22/98:261100007.
1997–2002	Material models of concrete for the assessment of severe accidents in nuclear industry. Project of Grant Agency of Czech republic GACR 103/97/K003.
2000–2002	Risk assessment of structures - the loss of load-bearing capacity and serviceability of thin-walled structures, Project of the Grant Agency of Czech republic GACR 103/00/0603
2002–2004	Nonlinear Fracture Mechanics of Concrete with Utilization of Stochastic Finite Elements and Random Fields. Project of the Grant Agency of Czech republic GACR 103/02/1030
2001–2003	SARA: Structural Analysis and Reliability Assessment, International project of Brno University of Technology (Czech Republic), BOKU Vienna (Austria), Cervenka Consulting Prague (Czech Republic), TU Vienna (Austria), and University Trento (Italy).
2004–now	Model identification and optimization at material and structural levels. Project of the Grant Agency of Czech republic GACR 103/04/2092
01/2003–03/2003	Grant of German Science Foundation (DFG) in the framework of the Collaborative Research Center 532.
03/2004–04/2004	U.S. National Science Foundation under grant CMS-9713944 to Northwestern University NU (Prof. Z.P. Bažant)

Brno, September 20, 2004