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Probabilistic analysis of concrete cracking using neural networks and random fields

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Abstract

In this paper an algorithm for the probabilistic analysis of concrete structures is proposed which considers material uncertainties and failure due to cracking. The fluctuations of the material parameters are modeled by means of random fields and the cracking process is represented by a discrete approach using a coupled meshless and finite element discretization. In order to analyze the complex behavior of these nonlinear systems with low numerical costs a neural network approximation of the performance functions is realized. As neural network input parameters the important random variables of the random field in the uncorrelated Gaussian space are used and the output values are the interesting response quantities such as deformation and load capacities. The neural network approximation is based on a stochastic training which uses wide spanned Latin hypercube sampling to generate the training samples. This ensures a high quality approximation over the whole domain investigated, even in regions with very small probability.
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Keywords: Random fields; Artificial neural networks; Response surfaces; Latin hypercube sampling; Stochastic training; Cohesive cracks

1. Introduction

Estimating uncertainties is an important task in the design process for engineering structures. While the standard way using safety factors according to the valid design code is applied in most practical cases, a newer development using an explicit stochastic modeling of the uncertainties in the loading, geometrical, and material properties becomes more and more attractive as it designs more efficient structures.

Several procedures have been developed for a stochastic analysis. A simple method is the description of such uncertainties by a set of correlated random variables, where each variable represents a material parameter, load factor, or geometrical property. Such an approach is used for example in [1,2] for the analysis of concrete bridges.

A more detailed method assumes a spatial distribution of geometrical or material properties and models this random distribution by a continuous field called a random field. In combination with the finite element method this approach is generally called the stochastic finite element approach [3,4]. Fluctuations of material properties of steel structures were investigated for example in [3,5]; the latter study simulates discrete crack growth using the element-free Galerkin method. Similar analyses have been carried out for concrete structures in [6], where the cracking of the material was considered by means of predefined cohesive interfaces.

Stochastic modeling of structures is generally performed in order to determine the probabilistic response or to assess reliability. Different procedures are usually applied in the two cases. In the reliability analyses of engineering structures generally very small failure probabilities have to be estimated. In principle plain Monte Carlo Simulation (MCS) is suitable for this task, but a large number of samples is required. Several much more efficient methods have been developed for this purpose. Two of these sampling strategies are importance sampling [7] and adaptive sampling [8], which are improved Monte Carlo simulations choosing a sampling distribution different from the original distribution. Thus during the stochastic simulation a large fraction of realizations will be obtained in the failure domain and the probability of failure can

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be estimated very well with a much smaller number of samples. Other methods are the first- and second-order reliability methods, where the limit state function is approximated by a linear or quadratic expression. For the investigation of complex nonlinear systems the reduction of the number of required evaluation points could be necessary. This is achieved by using an approximation of either the performance function or the limit state function. A powerful and widely used approach to such an approximation is the Response Surface Method (RSM) [9,10], where mostly a polynomial regression of the evaluated values is used for the reliability analysis.

In recent years artificial neural networks (ANN) have been applied in several studies for this purpose, e.g. in [11–17]. In these studies the structural uncertainties in material, geometry and loading have been modeled by a set of random variables. A reliability analysis has been performed either approximating the structural response quantities with neural networks and generating ANN based samples or by reproducing the limit state function by an ANN approximation and deciding for the sampling sets upon failure without additional limit state function evaluations. The main advantage of ANN approximation compared to the RSM is the applicability to higher dimensional problems, since the RSM is limited to problems of lower dimension due to the more than linearly increasing number of coefficients. In [18] firstly a neural network approximation of the performance function of uncertain systems in the presence of random fields was presented, but this approach was applied only for simple one-dimensional systems.

For the analysis of concrete structures the detailed representation of a very complex process, the cracking in a cohesive material, is very important. In this study discrete crack growth is modeled using a meshless discretization to represent the expanding discontinuity lines. In order to describe the complex cracking process on the macroscale the fictitious crack model [19] is applied. On the basis of a random field modeling of the material fluctuations of the correlated concrete parameters, the important response quantities such as deformations, ultimate load and post-peak load–displacement curves are approximated by neural networks. In order to reduce the number of random variables, which are handled as input values for the neural network, the random field is spectrally decomposed according to [3]. An improved stochastic training is presented, where an optimal approximation is achieved using stretched Latin hypercube sampling. The performance of the this approximation technique is shown for several numerical examples.

2. Simulation of concrete cracking

In this work a meshless interpolation scheme is used for the representation of growing crack discontinuities, where the interpolation function depends only on the nodal positions. Most meshless interpolation functions can represent continuous stress functions which enables an easy state variable transfer and a more accurate evaluation of a crack criterion even for coarse discretization levels. As the meshless interpolation the natural neighbor interpolation [20] is utilized in the framework of a Galerkin approach [21].

The natural neighbor interpolation is based on the Voronoi diagram and its dual Delaunay tessellation of the domain. Both can be defined for an arbitrary set of nodes in the m-dimensional space. In this study this concept is realized in a two-dimensional framework. The application of this interpolation scheme in a Galerkin approach is called the natural neighbor Galerkin method or Natural Element Method (NEM) [21]. This method shows several advantages compared to the common element-free Galerkin method [22], such as the automatic fulfillment of the essential boundary conditions. The NEM shape functions have compact support and the interpolation fulfills the partition of unity condition and linear completeness is satisfied [21]. More details about the application of the natural neighbor interpolation for discrete crack growth modeling can be found in [23,24].

Due to the flexible shape function formulation meshless methods are in general more computationally expensive than standard finite elements methods. Thus in this work an adaptively coupled discretization is applied, where finite elements are used in the parts of the structure without cracking and the meshless interpolation is used in the cracked regions.

The cohesive crack behavior of concrete is modeled using the fictitious crack model [19]. In this model the fracture process zone ahead of a real crack tip is lumped into a fictitious crack line transferring surface stresses until the crack width reaches a critical value. In this study the cohesive forces are transmitted via finite interface elements with linear shape functions, which are placed automatically between the new crack surfaces. The interested reader is referred to [23] where more details of the cohesive crack growth algorithm can be found.

3. Modeling of material uncertainties using random fields

A random field H can be interpreted as geometrically multi-dimensional stochastic process, which can be described in a domain D as

$$\{H(\mathbf{x}); \mathbf{x} \in D \subseteq \mathbb{R}^n\}. \tag{1}$$

The dimension n of the geometrical space can be arbitrary. In this study a two-dimensional representation is used and the applied random fields are assumed to be weakly homogeneous and isotropic. The correlation of the random field is defined by the autocorrelation function R_{HH} which is assumed here to be of exponential type.

In this study the integration point method [3] is used to discretize the random fields, where the uncertainties are represented at the Gaussian integration points. There the number of these points is equivalent to the number of random variables. The discretized value at a point i is then directly given as

$$H_i = H(\mathbf{x}_i) \tag{2}$$

and the number of random variables $H_i = H(\mathbf{x}_i)$ of the discretized random field can be written in a random vector

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