



Random finite element method for the seismic analysis of gravity dams

M.A. Hariri-Ardebili^{a,b,*}, S.M. Seyed-Kolbadi^b, V.E. Saouma^{a,b}, J. Salamon^c, B. Rajagopalan^a

^a Department of Civil Environmental and Architectural Engineering, University of Colorado, Boulder, USA

^b X-Elastica, LLC, Boulder, USA

^c US Bureau of Reclamation, Denver, CO, USA

ARTICLE INFO

Keywords:

Uncertainty
Heterogeneous
Seismic
Probabilistic
Dam class
Concrete

ABSTRACT

The seismic response of gravity dams is typically derived under a deterministic finite element model for the dam-reservoir-foundation system. In the case where uncertainty in material properties should be incorporated into overall dam performance, the sensitive parameters can be treated as random variables. This paper presents the results of a study that considers the spatial distribution of random variables in the context of random field theory.

Koyna Gravity Dam is used as a setting for numerical simulations. The concrete modulus of elasticity, mass density and tensile strength are all assumed to be random fields and generated based on the covariance matrix decomposition and midpoint discretization techniques.

The anatomy of the random field seismic responses are presented first, followed by a set of parametric analyses. The impact of correlation length, a single- vs. double-random field, one- or two-dimensional material distributions, ground motion intensity and record-to-record variability and, lastly, dam class are all investigated herein. The uncertainty and dispersion of the seismic responses are quantified in each model; it is found that concrete heterogeneity affects the seismic performance evaluation and should be considered in a structural assessment and risk analysis.

1. Introduction

1.1. Conceptual review

In general, the methods applied in structural analysis and design can be classified as either deterministic or probabilistic simulations. In the case where the finite element method (FEM), used to discretize the medium, is combined with statistics and reliability methods, the so-called probabilistic finite element method (PFEM) can be developed and applied to both linear and nonlinear systems. Based on the definition in Der Kiureghian and Ke [1], the term probabilistic or stochastic finite element method (SFEM) is employed in reference to a method that accounts for the geometric or material uncertainties in the structure, as well as the applied loads.

The Monte Carlo Simulation (MCS) family is the basic method used to perform a PFEM/SFEM analysis; it includes a repetition of the simulation observed from a stochastic process in order to determine the probability of occurrence of a certain limit state (LS). Since it is based on the theory of large numbers, $N_{\text{sim}} \rightarrow N_{\infty}$, an unbiased estimator of P_{LS} is given by:

$$\hat{P}_{\text{LS}}^{\text{MCS}} = \frac{N_{\text{exc}}}{N_{\text{sim}}} \quad (1)$$

where N_{sim} and N_{exc} are the total number of simulations and the number of exceeded samples, respectively; the “hat” indicates an estimation.

MCS-based SFEM includes the following steps:

- A number of random variables or random fields are generated as input for the SFEM. Note that the term “random variable” is used here for probabilistic simulations in which the property has a constant value over the entire model, while in the case of a “random field”, the parameter has (temporal or spatial) variability within the model.
- Run the finite element model for every random variable or random field.
- Extract the engineering demand parameter (EDP) as is customary in earthquake engineering (EE) or quantity of interest (QoI), which is the terminology used in uncertainty quantification (UQ). Next, perform a statistical analysis on the EDP/QoI to determine the appropriate distribution model.

The crude MCS, Eq. (1), requires many simulations, which

* Corresponding author at: Department of Civil Environmental and Architectural Engineering, University of Colorado, Boulder, USA.
E-mail address: mohammad.haririardabili@colorado.edu (M.A. Hariri-Ardebili).

introduces inefficiency in many large-scale, real-world finite element simulations. A wide array of methods have been proposed to reduce the number of samples, which in turn reduces the variance of the responses. Among these methods are: Importance Sampling (IS) [2], Latin Hypercube Sampling (LHS) [3], Subset Simulation (SS) [4], and design of experiments (DOE) [5].

Other techniques applied to computationally intensive systems are:

- Perturbation method, in which the random functions (e.g. stochastic finite element matrix, the loading vector) are expressed as the sum of deterministic and random components [6]. A Taylor series expansion can be used for this purpose, where higher-order terms improve the accuracy of the approximation. Various techniques within this category are aimed at calculating the first two moments of responses, i.e. the mean, variance and correlation coefficients [7].
- Spectral Stochastic Finite Element Method (SSFEM), in which the random field is expressed based on polynomial chaos expansion (PCE) and Karhunen Loève expansion (KLE) [8].
- Finite Element Reliability Method (FERM), in which the failure probability of the system is evaluated subject to a limit state (LS) function [9].

1.2. Literature review

Random field theory and its applications are extensively used in the field of geotechnical engineering [10]. Emphasis is placed on the slope reliability analysis based on random FEM [11,12]. Nour et al. [13] studied the probabilistic seismic response of a heterogeneous soil profile with three parameters (i.e. shear modulus, damping, and Poisson's ratio) as the spatially random fields. These authors found that heterogeneity greatly affects the behavior of the soil profile, which induces differential movement at the ground surface.

In the field of structural engineering, various researchers have investigated the impact of a heterogeneous quasi-brittle material (more specifically concrete) on the cracking response. Yang and Xu [14], Yang et al. [15] and Su et al. [16] investigated complex cohesive fracture in random heterogeneous quasi-brittle materials using the Monte Carlo simulation technique. Yin et al. [17] and Yin et al. [18] studied the fracture behavior of a random heterogeneous asphalt mixture with a cohesive crack.

In the case of concrete dam engineering, studies are very limited. The only research papers accessible are Tang et al. [19], Zhong et al. [20] and Yin et al. [21]. In all of these, concrete heterogeneity has been modeled based on the Weibull distribution law, while damage plasticity is used to simulate the failure process. These authors reported that when concrete heterogeneity is considered, the stress distribution is no longer smooth, which therefore better reflects the real-world situation. Moreover, the concrete cracking pattern is qualitatively compared. They also showed that different samples with the same heterogeneity index lead to a similar crack pattern; however, no statistical interpretation is drawn. Increasing the heterogeneity index (i.e. more homogeneous concrete), increases the potential for localized damage, and increases the risk of damage under seismic excitation.

1.3. Objectives and contributions

The objective of this paper is to study the seismic response of concrete gravity dams according to random field theory. A basic formulation for random fields will be reviewed first (Section 2). Second, the numerical model for the dam case study will be explained (Section 3). Next, a brief overview will be provided on the seismic performance index used in this paper (Section 4). Lastly, the anatomy of these random field responses plus a set of parametric and sensitivity analyses will be presented in Section 5.

Some of the authors' major contributions can be summarized as follows:

- Formulation of random field theory for the time history elastic properties of gravity dams.
- Evaluation of the correlation length effect on response dispersion.
- Evaluation of both single- and double-random field distributions on the dam response.
- Quantification of the degree of spatial distribution on response dispersion.
- Study of the impact of ground motion intensity on response dispersion.
- Quantification of ground motion record-to-record variability and local/spatial material randomness on response dispersion.
- Investigation of the impact of dam class (e.g. shape and size) on response pattern.

2. Random fields

2.1. Random field classifications

According to Vanmarcke [22], differences between the types of random fields originate from the nature of the uncertainty within the studied stochastic environment. Uncertainty about the properties of a random medium is categorized in the passive type of field. However, a space-time process, $H(\mathbf{x}, \mathbf{t})$, is characterized by both active and intrinsic uncertainties. On the other hand, depending on the locations of observation points, a random field can be classified into one of five groups, namely:

- Random series: observations are recorded at discrete points along a time axis, Fig. 1(a).
- Lattice process: observations are recorded at the sites of a spatial lattice, Fig. 1(b).
- Continuous random function: observations are recorded at all points along a spatial and/or temporal coordinate axis, Fig. 1(c).
- Random partition of space: the random discrete variable is observed at every point in space, Fig. 1(d).
- Random point process: points are located according to a random pattern in space, Fig. 1(e).

2.2. Random field generators

In an interesting classification, Van der Have [23] provided a comprehensive review of some of the most widely used techniques for generating random fields. Two classes basically exist, Fig. 2:

- Class I: This class consists of a spatially-correlated random variable and a discretization method. For every point in the finite element domain, a random variable correlated with other points in the random field domain is generated. The evaluated points could be: element integration points, nodes, or representative points (e.g. an element center).

The discretization techniques can also be divided into three main categories, Fig. 2:

- Point discretization methods, resulting in a piecewise constant random field; these include the MPM and IPM.
- Point discretization methods, resulting in a continuous random field; these include the SFM and OLE.
- Average discretization methods, including the SAM and WIM.
- Class II: This class is based on series expansion methods, wherein the random field is represented by a sum of functions that are multiplied by a random variable. This class generates a continuous random field. To be applied in a finite element mesh, these continuous

Download English Version:

<https://daneshyari.com/en/article/6736256>

Download Persian Version:

<https://daneshyari.com/article/6736256>

[Daneshyari.com](https://daneshyari.com)