Engineering Structures 146 (2017) 118–126

Contents lists available at ScienceDirect

Engineering Structures

journal homepage: www.elsevier.com/locate/engstruct

Entropy-based sensitivity analysis of global seismic demand of concrete structures

Azad Yazdani [a,*], Ahmad Nicknam [b], Ehsan Yousefi Dadras [b], Seyed Nasrollah Eftekhari [c]

[a] Department of Civil Engineering, University of Kurdistan, Sanandaj, Iran
[b] School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran
[c] Faculty of Technology and Mining, Yasouj University, Choram, Iran

ARTICLE INFO

Article history:
Received 17 June 2016
Revised 25 March 2017
Accepted 11 May 2017

Keywords:
Sensitivity analysis
Concrete structures
Entropy
Ground-motion simulation
Uncertainty

ABSTRACT

This study presents a global sensitivity analysis approach based on entropy to investigate the influence of excitation and structural parameters on the engineering demand parameters. The sensitivity of the nonlinear dynamic structural response using synthetic earthquake ground motions to major uncertain sources, propagation paths and site variables of the simulated ground motion, and physical characteristics of the structures is investigated using an entropy-based sensitivity index as a measure of importance to determine which variables are most significant. The results show that the uncertainties of ground-motion variables are more significant than those in the structural properties. The greatest contributor to the variability in the seismic demand is the uncertainty in earthquake source parameters. Our analysis also revealed that viscous damping is the most important structural source of variability in seismic structural demands. Structural dynamic analysis due to simulated excitation opens the door for the wider use of seismological theory to understand the relationship between the structural response and seismological variables.

1. Introduction

Uncertainty poses one of the greatest challenges to the evaluation of building performance under seismic loading and is generally costly in earthquake engineering. The main sources of uncertainty in earthquake engineering include the lack of knowledge of future ground motions and variability in the physical characteristics of structures. Reducing uncertainty in each of these different sources can help reduce cost.

Sensitivity analysis (SA) is an important task in earthquake engineering. SA is typically used to increase the understanding of the relationships between input variables and output in a computational model and the relative contribution of each input variable to the uncertainty in the model output [1]. Thus, the variables that do not contribute substantially to the model uncertainty can be fixed as their best estimates rather than treated as random to simplify the analysis. In addition, the variables that cause significant variability in the output can then be the focus of attention so that they are better understood, thereby reducing the variability of the output. Usually, SA methods are classified into local and global methods. Generally, local SA methods have some key limitations. In these methods, the sensitivity study is conducted at the central estimate of input variables, whereas the results could be quite different at other points. Additionally, local SA methods rank the input parameters in order of significance, but do not quantify how much a given parameter is more important than another. In contrast, global SA methods apportion the output variability to the variability of the input variables when they vary over the whole uncertainty domain [2]. Using the global SA approach, the quantitative relative importance of each input variable as well as the influence of key variables can be measured in terms of the demand.

The sensitivity of seismic demand to the uncertain variables has been studied by several authors. However, the focus of the majority of these studies has concentrated on approximate or local SA methods [3–7]. Additionally, in most previous studies, uncertainties in ground motion are commonly represented by a site-specific hazard curve of intensity measure and record-to-record variability [8–10]. This representation suffers from concerns regarding the lack of available recorded strong motion data. Moreover, the selected ground motion records should generally be scaled and/or modified to make them more representative of the target condition. This manipulation changes the relationship between the characteristics of the recorded ground motions and

* Corresponding author at: Department of Civil Engineering, University of Kurdistan, P.O. Box 416, Sanandaj, Iran.
E-mail address: a.yazdani@uok.ac.ir (A. Yazdani).

http://dx.doi.org/10.1016/j.engstruct.2017.05.023
0141-0296/

their original physical conditions and may render motions with unrealistic characteristics [11].

This paper aims to assess the relative contribution of different sources of uncertainty, including ground motion variables and structural properties on the inelastic response of concrete structures using a global SA method. Here, we propose to apply a global SA method based on information theory, which uses entropy as a sensitivity measure [12]. The entropy-based global SA method can reveal complementary or additional information compared to the most often applied variance-based method [13]. As an alternative approach to the use of past earthquake records, we simulate realistic synthetic seismograms based on the stochastic finite-fault ground motion simulation technique [14–15]. One advantage of ground-motion simulation is that the synthetic time series result from a given earthquake scenario and do not need to be scaled or modified for any further applications. Furthermore, using ground motion simulation methodology, we can separate the influences of seismic sources, wave propagation, and local geological condition variables.

2. SA methodology

SA is an efficient tool to study the behavior of a model and to determine the significance of each input parameter to the model output uncertainty. Although many of the previous global SA studies were performed based on variance-based methods [16–17], in which the variance of output is decomposed as a sum of the contributions of each input variable, these methods have some well-known limitations [18]. The main challenge for implementing variance based SA is that it is typically needed to run the model many times using some sampling methods. This restricts the use of variance-based methods for SA of complex computer codes and slow-to-evaluate models that require a long time for a single run.

In this study, we used an alternative SA approach based on information-theoretic tools to quantify the relationship between the input parameters and the output distribution [12,19]. This global SA method is suitable for cases where the model is expensive to evaluate. Also the entropy-based global SA method takes into account situations where variance is not well adapted [13].

Let the simulation model be written as $Y = f(\boldsymbol{X})$, where $\boldsymbol{X}$ contains the random input and system parameters $\{X_1, X_2, \ldots, X_n\}$ that are used to generate the response function $f(\boldsymbol{X})$. The model f maps elements of the vector $\boldsymbol{X}$ to output Y. Because $\boldsymbol{X}$ is random, Y is random in general. In information theory, entropy measures the amount of uncertainty of an unknown or random quantity [20]. The entropy of a discrete random variable Y with probability mass function $p(y)$is defined as

$$H(Y) = -\sum_{yY} p(y) \log p(y) \tag{1}$$

Entropy is a function of the probability mass function p and does not depend on the values of Y. This is a notable difference with using the variance as an uncertainty indicator, which is computed by taking the sum of squares of the deviations. Entropy is a quantitative measure to assess uncertainty in a single random variable. Entropy $H(Y)$ is zero when Y is deterministic, and reaches a maximum value for uniform distributions. The concept of entropy can be extended to a pair of random variables. For conditional entropy, $H(Y|X_i)$, which indicates the degree of uncertainty, given knowledge of one of the input parameters $X_i$in the output Y, we have:

$$H(Y|X_i) = -\sum_{x\varepsilon X_i}\sum_{y\varepsilon Y} \mathrm{p}(y,x) \log\{p(y|x)\} \tag{2}$$

where $p(x,y)$ is the joint probability distribution function of X_i and Y, and $p(y|x)$ denotes the conditional density of y given x. $H(Y|X_i)$ defines the average loss of information of Y when the behavior of a random variable X_i is known.

Based on these definitions, the mutual information between two random variables is a quantity that measures their mutual dependence. The mutual information $I(Y, X_i)$ between two random vectors X_i and Y is defined by

$$I(Y, X_i) = \sum_{x\varepsilon X_i}\sum_{y\varepsilon Y} p(y,x) \log\left(\frac{p(y,x)}{p_{\mathrm{Y}}(y)p_{X_i}(x)}\right) = H(\mathrm{Y}) - H(Y|X_i) \tag{3}$$

where $p_{X_i}(x)$ and $p_Y(y)$ are the marginal densities for X_i and Y, respectively. The mutual information measures how much knowing the input parameter X_i reduces uncertainty about the output Y. Mutual information equals zero if and only if X_i and Y are independent. A low mutual information value represents that knowing X_i reveals little about the value of Y, whereas a high mutual information value represents that knowing X_i reveals considerable information about the value of Y. Because this quantity measures the mutual dependence between two random variables, it is useful to exploit it for our task of SA. Krzykacz-Hausmann [12] defined the information-theoretic-based sensitivity index as:

$$\eta_i = \frac{I(Y, X_i)}{H(Y)} = 1 - \frac{H(Y|X_i)}{H(Y)} \tag{4}$$

which is a representation of the information learned about Y based on the knowledge of X_i. This index is taken as a measure of importance of the random input variables in this study.

In practice, the model could be run with the dataset of input excitation and structural parameters, so the interested output (seismic structural demands in this study) can be determined. By repeating this procedure multiple times using the MC simulation method, a dataset of input variables and their corresponding outputs are achieved. Eventually, the standard methods for the estimation of entropy and mutual information can be used to determine the rate of decline of the output entropy as a result of having knowledge about each of the input random variables.

3. Stochastic ground motion simulation model

Stochastic ground motion simulation is widely used to simulate acceleration time series for use in engineering applications [21,22]. In the absence of significant locally recorded strong motion data, such simulated motions can be used in the reliability assessment of structures. The stochastic finite-fault simulation model, which is able to characterize key features of the earthquake source process and wave propagation, is used to simulate strong ground motions [14,23].

In the stochastic finite-fault method, the fault plane is divided into a number of sub-faults, and each sub-fault is represented as a point source. Using the seismological model of Boore [24], the ground motion contributions from each sub-fault is calculated stochastically. The simulated synthetic time histories of all the point sources are summed up at the observation point by applying time delays. In this approach, the acceleration spectrum of the shear waves for horizontal ground motions due to ij^{th} sub-fault, $A_{ij}(f)$, may be modeled as follows:

$$A_{ij}(f) = (CM_{0ij}H_{ij}(2\pi f)^2/[1 + (f/f_{0ij})^2]) \exp(-\pi f R_{ij}/Q(f)\beta) \times \exp(-\pi f \kappa) G(R_{ij}) D(f) \tag{5}$$

where M_{0ij},f_{0ij} and R_{ij} are the ij$^{\mathrm{th}}$ sub-fault seismic moment, corner frequency and the hypocentral distance from the observation point, respectively. H_{ij} is a scaling factor to conserve the high-frequency spectral level of the sub-faults. The corner frequency is given by $f_{0ij} = 4.9 \times 10^6 \beta(\Delta\sigma/M_{0ij})^{1/3}$, where $\Delta\sigma$ is the stress parameter in bars, M_{0ij} is in dyne centimeters, and β is the shear-wave velocity