Reliability Engineering and System Safety 117 (2013) 9–20

Contents lists available at SciVerse ScienceDirect

Reliability Engineering and System Safety

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

Sensitivity measures for optimal mitigation of risk and reduction of model uncertainty

M. Mahsuli [a,*], T. Haukaas [b]

[a] Department of Civil Engineering, Sharif University of Technology, Azadi Ave., Tehran, Iran
[b] Department of Civil Engineering, University of British Columbia, 6250 Applied Science Lane, Vancouver, BC, Canada V6T 1Z4

ARTICLE INFO

Article history:
Received 30 August 2012
Received in revised form
18 March 2013
Accepted 21 March 2013
Available online 9 April 2013

Keywords:
Sensitivity analysis
Reliability methods
Probabilistic models
Risk mitigation
Model uncertainty
Software

ABSTRACT

This paper presents a new set of reliability sensitivity measures. The purpose is to identify the optimal manner in which to mitigate risk to civil infrastructure, and reduce model uncertainty in order to improve risk estimates. Three measures are presented. One identifies the infrastructure components that should be prioritized for retrofit. Another measure identifies the infrastructure that should be prioritized for more refined modeling. The third measure identifies the models that should be prioritized in research to improve models, for example by gathering new data. The developments are presented in the context of a region with 622 buildings that are subjected to seismicity from several sources. A comprehensive seismic risk analysis of this region is conducted, with over 300 random variables, 30 model types, and 4000 model instances. All models are probabilistic and emphasis is placed on the explicit characterization of epistemic uncertainty. For the considered region, the buildings that should first be retrofitted are found to be pre-code unreinforced masonry buildings. Conversely, concrete shear wall buildings rank highest on the list of buildings that should be subjected to more detailed modeling. The ground shaking intensity model for shallow crustal earthquakes and the concrete shear wall structural response model rank highest on the list of models that should be prioritized by research to improve engineering analysis models.

1. Introduction

The primary objective in this paper is to guide the allocation of resources for civil infrastructure subjected to multiple hazards. This addresses one of the great challenges faced by the modern society: Limited resources must be prioritized to mitigate risk and/or improve the understanding of risk. To this end, three different but complementary questions are asked and addressed: (1) Which infrastructure components should be prioritized for seismic retrofit to mitigate seismic risk? (2) Which infrastructure components should be subjected to detailed modeling to reduce the epistemic uncertainty in order to improve the quality of the risk analysis? and (3) Which models should be prioritized in research to reduce the epistemic uncertainty to improve the quality of future risk analyses? All three questions deal with the general problem of distributing limited resources in an optimal manner under conditions of uncertainty. Therefore, although the presented application is specific to structural earthquake engineering, the developments are broadly applicable.

In the past, earthquake engineering focused on structural responses [1,2]. Seismic risk analysis aimed at computing the probability of structural failure, where failure was defined as the exceedance of certain response thresholds. In modern earthquake engineering, the seismic risk is quantified by cost probabilities [3]. In this context, the range of consequences is not limited to structural failure, and includes damage and economic impacts. Thus, the primary result from the risk analysis is the cost exceedance probability curve, or selected points on it. A version of this curve that omits retrofit cost is sometimes referred to as a "loss curve," which forms an important basis for decision-making in the insurance industry [4]. Loss curves are also central in contemporary performance-based earthquake engineering [5]. In the example presented later, the cost has two causes: repair of damage after an earthquake and cost of *a priori* retrofit actions.

The vehicle for the developments presented here is the computation of cost exceedance probability curves by reliability methods. This contrasts with many contemporary seismic risk analysis approaches that employ total probability integration with conditional probability models [6,7]. Reliability analysis requires the specification of a limit-state function, g, because reliability methods are designed to estimate the probability that $g \le 0$. Therefore, to compute the probability that the total cost, c, exceeds a threshold, c_t, the following limit-state function is specified

$$g = g(\boldsymbol{\theta}, \mathbf{x}, \mathbf{v}) = c_t - c(\boldsymbol{\theta}, \mathbf{x}, \mathbf{v}) \quad (1)$$

where $\boldsymbol{\theta}$ = vector of "epistemic random variables," $\mathbf{x}$ = vector of "aleatory random variables," and $\mathbf{v}$ = vector of decision variables that

* Corresponding author. Tel.: +98 21 6616 4201.
E-mail addresses: mahsuli@gmail.com, mahsuli@sharif.edu (M. Mahsuli), terje@civil.ubc.ca (T. Haukaas).

0951-8320/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.ress.2013.03.011

are at the discretion of the decision maker. The phrase epistemic is employed to identify random variables that have a probability distribution that changes when new data or new research emerge. In contrast, aleatory random variables represent irreducible uncertainty. The motive behind this categorization is that it permits targeted efforts to reduce uncertainty [8]. In fact, this study first establishes a framework of models that explicitly include epistemic uncertainty. Thereafter, sensitivity measures are developed to guide the allocation of resources to reduce that uncertainty.

The central theme of this work is sensitivity analysis. A review of the contemporary articles on this topic is presented in [9]. Sensitivity analysis methods are categorized into “local” and “global” [10]. Local sensitivity analysis, employed here, computes the partial derivatives of the outputs with respect to input parameters. It is also noted that the utilization of local sensitivity analysis for decision support is not new. For instance, Der Kiureghian et al. [11] developed closed-form expressions for the sensitivity of performance measures of a system with respect to the mean rate of failure and the mean duration of repair of each component to prioritize the components for retrofit. Furthermore, several past studies employed sensitivity analysis to identify the most influential parameters on the seismic response of structures [12–15]. These studies focus on the computation of structural response probabilities, and carry out the sensitivity analysis by either parametric study or analysis of variance. The approach here contrasts with these studies in several aspects: (1) It identifies the models that are most influential on the risk estimates; (2) It conducts sensitivity analysis by computing derivatives; (3) It goes beyond structural response and computes the sensitivity of cost probabilities; and (4) It is applicable to a portfolio of structures subjected to multiple hazards.

Prioritization of infrastructure for seismic retrofit is another relevant field of research. The Applied Technology Council [16] put forward a framework to rank a building inventory by subjective assessment of the building importance, followed by an analytical estimation of strength. Grant et al. [17] proposed a prioritization scheme for seismic retrofit of school buildings in Italy. They narrowed down the list of buildings that should be subject to retrofit through vulnerability assessments by visual inspection, followed by simplified structural analyses. Tesfamariam and Saatcioglu [18] developed a fuzzy approach to rank reinforced concrete buildings according to seismic performance. Neither of these methodologies employs sensitivity analysis for ranking the buildings. In contrast, the present study prioritizes the buildings according to the amount of reduction in the regional risk per dollar spent on retrofit.

In the following, first a brief overview of the models that are utilized and the analysis approach is presented. Next, three sensitivity measures are presented, which address the three questions posed earlier. Each sensitivity measure is utilized in a comprehensive analysis of the 622 buildings on the campus of the University of British Columbia (UBC) in Vancouver, Canada. An array of models is employed to compute costs, with models ranging from earthquake magnitude to cost of retrofit. Moreover, the region is subjected to several sources of seismicity. To facilitate reliability analysis with this many interacting models, the authors have developed a new computer program, called Rt. This program comprises a comprehensive library of probabilistic models. The software architecture to support multi-model reliability and optimization analysis is presented in [19] and new developments in the modeling and analysis are presented here. Rt is freely available online at www.inrisk.ubc.ca.

2. Models

The approach adopted in this paper has two components: probabilistic models and reliability methods. The models produce scalars or vectors of physical responses, and all the uncertainty is described by random variables. A simple but instructive model is the linear regression model

$$y=\theta_1+\theta_2\cdot h_2(\mathbf{x})+\theta_3\cdot h_3(\mathbf{x})+\cdots+\varepsilon \tag{2}$$

where y=model response, θ_i=model parameters, $h_i(\mathbf{x})$=explanatory functions, and ε=zero-mean normally distributed model error. In the Bayesian approach to linear regression, the parameters θ_i, as well as the standard deviation of ε, denoted by σ_ε, are random variables. This approach is adopted here, and the model parameters are categorized as epistemic random variables, i.e., $\boldsymbol{\theta}=\{\theta_1, \theta_2, \ldots, \varepsilon\}$. Importantly, their probability distribution is affected by model improvement efforts, typically data-gathering. Box and Tiao [20], Gardoni et al. [21], and others describe the statistical inference to obtain the probability distribution for $\boldsymbol{\theta}$. The Bayesian philosophy, in which the model uncertainty is explicitly included, is employed throughout this study, regardless of model form.

Table 1 provides an overview of the regression models that are utilized in the numerical example. They predict the intensity of ground shaking and the response and damage of buildings. Some of the models are from the literature and others are created inhouse. It is impractical to describe all the models in detail here, but the first two columns in Table 1 provide the name and the number of instances of each model in the numerical example. The third column in Table 1 show the number of model variables, $\boldsymbol{\theta}$, and the last column shows the value of a sensitivity measure that will be discussed in Section 6.

The models in Table 1 are employed in reliability analysis to compute cost exceedance probabilities for the UBC campus. Fig. 1 pinpoints this region in the Google Maps® interface in Rt. The markers in the zoomed map of the UBC campus identify the 622 considered buildings. 26 of the buildings are numbered in Fig. 1 because they appear prominently in the rankings that are presented later. To provide an outline of the information that is available for each building, Table 2 displays selected information for the 26 buildings that are numbered in Fig. 1.

The UBC campus is subjected to three sources of seismicity: Shallow crustal earthquakes, deep subcrustal earthquakes, and megathrust subduction earthquakes. The first two are modeled as area sources, while subduction earthquakes originate from a line source [22]. Earthquake events in each area source are represented by rupture points that are equally likely to happen anywhere within that source. The modeling of the rupture in the subduction line source is described shortly. Fig. 2 shows the location of the earthquake sources relative to the UBC campus. In this figure, area sources are divided into several sub-areas. Specifically, the crustal earthquake source is divided into six area sources and the subcrustal area source is divided into three area sources. This is done because the first-order reliability method (FORM) [23] is employed, as described shortly, which requires the limit-state function in Eq. (1) to be continuously differentiable and relatively linear in the space of random variables. In particular, when the realization of the earthquake location nears the UBC campus, the earthquake intensity and the ensuing repair costs increase exponentially. This results in a sharp peak and thus a severe nonlinearity in the repair cost with respect to variables that describe the uncertain location of earthquakes. By breaking the area source at the centroid of the campus, the repair cost becomes relatively linear with respect to the location random variables for each subdivision. It is also noted that the subduction source is divided into two sources. Subduction Source 1 generates earthquakes of magnitude 8.0–8.9 [24]. These earthquakes have a limited rupture zone with unknown location, and are modeled by the line source shown in Fig. 2. In contrast, Subduction Source 2 generates earthquakes of magnitude 8.9–9.2, in which the entire subduction zone ruptures [24]. In this case, the location is not uncertain, and is