Vienna Congress on Recent Advances in
Earthquake Engineering and Structural Dynamics 2013 (VEESD 2013)
C. Adam, R. Heuer, W. Lenhardt & C. Schranz (eds)
28-30 August 2013, Vienna, Austria
Paper No. §§§

Robust Fragility Assessment using Bayesian Parameter Estimation

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Abstract. Analytical fragility curves corresponding to a prescribed limit state can be evaluated by propagating the various sources of uncertainty in the performance assessment of structures. This work proposes an efficient Bayesian parameter estimation method suitable for fragility curves based on a given probability model; in particular, the bi-parameter Log Normal probability distribution. This approach consists of Bayesian parameter estimation for the mean and the standard deviation of the Log Normal Fragility Model, given a limited (in the order of 10 to 50) number of structural analysis results for a specific structural performance variable denoted as Y. This leads to calculation of the robust fragility and its percentiles or plus/minus standard deviation confidence interval underlying the number of simulations/realizations. The application of the robust fragility method is investigated in two cases: (a) vulnerability assessment to flooding for a class of non-engineered structures; (b) seismic vulnerability assessment for an existing structure. . In case (a), the critical flooding height for collapse limit state is adopted as structural performance variable Y. In this case, the resulting fragility curves are validated with respect to the results of Standard Monte Carlo simulation. In case (b), the spectral acceleration value corresponding to a critical demand to capacity ratio of unity is adopted as the structural performance parameter Y for the near collapse limit state

Keywords: Performance-based engineering, Natural hazards, Uncertainty, Structural vulnerability, Analytic Fragility

1 INTRODUCTION

Simulation-based methods are quite efficient for propagating the uncertainties with the purpose of fragility assessment. However, they often involve a large number of structural analyses. This work presents an outlook into a bi-stage approach to analytic fragility assessment using Bayesian parameter estimation and based on a small number of simulations/structural analyses. In the first stage and starting from a prescribed analytic probability model for structural fragility, Bayesian parameter estimation is used in order to obtain the probability distributions for the fragility model parameters. In such context, the uncertainty characterization is performed by generating various realizations of the structural model and loading based on small-sample simulations by calculating a suitable structural performance parameter denoted generically as *Y.* The set of values obtained for the adopted structural performance variable are used next as *data* or information in order to update the *prior* distribution for the fragility model parameters, leading to the *posterior* probability distribution for the model parameters. In the second stage, large-sample Monte Carlo simulation is used to generate a set of plausible fragility curves, based on the prescribed analytical model. Finally, various percentile statistics of these fragility curves can be calculated. These percentiles reflect the uncertainty in estimating the modeling parameters and are a function of number of different realizations of structural performance variable and the sufficient statistics for the set of *Y* values. The application of this two-stage approach is demonstrated in two cases, namely, flood fragility assessment for a class of structures and seismic fragility assessment for a single structure.

1.1 Flooding fragility assessment

with regard to flood vulnerability assessment for single structures or a group of structures, many research efforts have been concentrated on creating a link between flooding intensity and observed damage to buildings in the aftermath of the flooding event (Smith, 1994, Kelman, 2002, Kang et al., 2005, Schwarz and Maiwald, 2008, Chang et al., 2009, Schwarz and Maiwald, 2012). On the other hand, many research efforts are starting to galvanize in the direction of proposing analytical models for flood vulnerability assessment taking into account the many sources of uncertainties (Nadal et al., 2009, DeRisi et al., 2013a).

1.2 Seismic fragility assessment

There are quite a few methods proposed for seismic fragility assessment, with various ranges of accuracy and amount of analysis efforts involved. For example, Schotanus et al. (Schotanus and Franchin, 2004) have used a response surface analysis together with the first order reliability method (FORM) in order to propagate the uncertainties. Jalayer et al. (Jalayer et al., 2007) have used the Bayesian updating for propagating the uncertainties in the ground motion and structural modeling. This includes creating a set of realizations of different structural models that are each subjected to a distinct real ground motion recording belonging to a set of selected records. This approach was further elaborated in the work by Jalayer et. al (Jalayer et al., 2011) in which the concept of robust fragility is introduced. Liel et al. (Liel et al., 2009) have used the response surface method in conjunction with Monte Carlo simulation in order to efficiently propagate the uncertainties. Vamvatsikos and Fragiadakis (Vamvatsikos and Fragiadakis, 2010) and Dolsek (Dolsek, 2009) have used Monte Carlo simulation and Latin hyper-cube sampling in order to propagate the various sources of uncertainties. Jalayer et al. (Jalayer et al., 2010) have used the Markov Chain Monte Carlo simulation in order to calculate the structural fragility (based on static analyses) by propagating the various sources of modeling uncertainties taking into account also the outcome of in-situ tests and inspections. In fact, the application of simulation-based methods for the calculation of seismic structural fragility might be limited by the fact that using stochastic ground motion records (i.e., ground motion records generating from a probability distribution) is less wide-spread compared to the use of real recorded ground motions. In fact, various methods are proposed in literature based on the application of real records (see for example, (Vamvatsikos and Cornell, 2004, Aslani and Miranda, 2005). One of the advantages the method proposed herein is that it can be used for seismic fragility assessment based on both real and stochastic ground motions.

2 METHODOLOGY

2.1 Structural Limit States, Performance Variable and Interface Variable

The analytical structural fragility can be defined as the probability of exceeding a prescribed *limit state* given a specific value of the fragility *interface variable* denoted as *IV*. This implies that each fragility curve corresponds to a specific structural limit state denoted as *LS*. The limit state exceedance can be expressed in terms of a structural performance variable (e.g., demand to capacity ratio, a damage index, inter-story drift, ..., etc.) denoted generically as *Y* exceeding the corresponding *LS* threshold. Herein, two different types of scalar and systemic parameters are adopted as the structural performance variable *Y*:

i) The critical demand to capacity ratio denoted as *Y* and defined as the demand to capacity ratio for the component that brings the system closer to failure. Herein, two alternative definitions of the critical demand to capacity ratio are used. The first one, which is based on the cut-set concept (Ditlevsen and Masden, 1996), is more suitable for cases where various potential failure mechanisms can be defined a priori (Jalayer et al., 2007):

$$Y_{LS} = \max_{l}^{N_{mech}} \min_{j}^{N_l} \frac{D_{jl}}{C_{jl}(LS)} \tag{1}$$

where N_{mech} is the number of considered potential failure mechanisms and N_l the number of components taking part in the l^{th} mechanism. D_{jl} is the demand evaluated for the *j*th component of the *l*th mechanism and $D_{jl}(LS)$ is the limit state capacity for the j^{th} component of the l^{th} mechansim. In the context of system reliability, a cut set can is defined as any set of components whose joint failure $Y(l)$ = min $D_{jl}/C_{jl} > 1$, implies failure of the system, Y = max $Y(l) > 1$. The second formulation used for the critical demand to capacity ratio is based on the concept of weakest link (DeRisi et al., 2013a):

$$Y_{LS} = \max_{s=1}^{N_{\sec}} \max_{j=1}^{N_s} \frac{D_{is}}{C_{is}\left(LS\right)} \tag{2}$$

where $N_{\sec}$ is the number of control sections in the structure and N_s is the number of subsections into which each section is divided. This definition may be suitable particularly for identifying the stress concentration (due to impact loading) in structures with brittle behavior.

b) The fragility interface variable corresponding to Y_{LS}=1; where Y_{LS} is the critical demand to capacity ratio defined as above. This structural performance variable is denoted generically as $IV^{Y=1}$. Using the *IV*-based representation of the limit state threshold can be quite advantageous as it does not have the non-convergence problems associated large displacements/rotations and its application does not require fitting a relationship between the performance variable Y_{LS} and *IV*. In fact, the use of *IV*-based limit state thresholds is already established and it examples can be found in various works such as (Jalayer and Cornell, 2003, Vamvatsikos and Cornell, 2004, Jalayer et al., 2007) and (Jalayer and Cornell, 2009). Later in this work, two examples of $IV^{Y=1}$ are presented for flooding and seismic excitation, namely, critical water height and the first-mode small-amplitude spectral acceleration corresponding to Y_{LS}=1.

2.2 The Concept of Robust Fragility

Suppose that the probability of exceeding a prescribed limit state *LS* given *IV* or the structural fragility *F*(*LS*) is described by a given analytical probability model (e.g., Normal, Log Normal, ..., etc.) with parameters $\boldsymbol{\chi}$ (e.g., median and logarithmic standard deviation for the Log Normal distribution). The expected value (or the *robust estimate*, Papadimitriou et al., 2001) for the probability of exceeding the limit state given a sample of structural performance variable $\boldsymbol{Y}$ values $\boldsymbol{Y}=[Y_i$: i = 1 : N] (later it is described how such a sample can be obtained) can be calculated as:

$$F\left(LS\,|\,Y\right) = \int_{\Omega(\boldsymbol{\chi})} F\left(LS\,|\,\boldsymbol{\chi}\right)\cdot p\left(\boldsymbol{\chi}\,|\,Y\right)\cdot d\boldsymbol{\chi} \tag{3}$$

Note that the dependence of the first term in the integral on *Y* is dropped assuming that $\boldsymbol{\chi}$ is sufficient statistics for relaying information about data *Y*, given the probability model chosen. $F(LS|Y)$ denotes the robust fragility or the conditional probability of exceeding the limit state for a given limit state *LS* given the sample of structural performance variable values *Y*; $\boldsymbol{\chi}$ is the vector of parameters that define the analytic probability; Ω is the space of possible values for vector $\boldsymbol{\chi}$; $F(LS|\boldsymbol{\chi})$ is the analytic fragility curve for a given vector of parameters $\boldsymbol{\chi}$; $p(\boldsymbol{\chi}|Y)$ is the joint probability density function (PDF) for vector $\boldsymbol{\chi}$ given the sample of values for the structural performance variable *Y*. Note that this PDF is calculated using the Bayesian probabilistic framework as a *posterior probability density* given the sample of values *Y*. The integral in Eq. (3) can be calculated numerically and using simulation-based methods.

2.3 The set of structural performance variables *Y*

Let vector $\boldsymbol{\theta}$ represent all the uncertain parameters taken into account in the problem. For example, this vector may contain structural analysis parameters, structural modeling parameters, mechanical material properties, and loading parameters. It is enough to note that any given realization $\boldsymbol{\theta}_i$ of vector $\boldsymbol{\theta}$ identifies in a unique manner the structural model and the loading parameters. Ideally, a standard Monte Carlo (MC) simulation scheme can be used for generating a set of *i*=1:*N* realizations of the vector $\boldsymbol{\theta}$. It is noteworthy that the different realizations of the vector $\boldsymbol{\theta}$ need not necessarily be generated from a probability distribution (as in the case of MC); rather, they need to represent independent observations (an assumption used later in the Bayesian inference). Therefore, even a set of recorded ground motions can be included within this vector in order to represent record-to-record variability. For example, the vector $\boldsymbol{\theta_i}$ can consist of a specific ground motion time-history plus a sample of MC realizations for structural modeling parameters. As it will be demonstrated later, it is possible to estimate the vector $\boldsymbol{\chi}$ based on a small set of realizations.

2.4 The Log Normal fragility model $F(LS|\chi)$

Suppose that the Log Normal fragility model is described by the vector of parameters $\boldsymbol{\chi}=[\mu, \beta]$. In this case the analytic fragility function can be described as:

$$F\left(LS \mid \chi\right) = P\left(IV^{Y(LS)=1} \leq IV \mid \mu,\beta\right) = \Phi\left(\frac{\ln IV - \mu}{\beta}\right) \tag{4}$$

where the parameters $\boldsymbol{\chi}=[\mu, \beta]$ stand for the mean and the standard deviation for the distribution of the natural logarithm of the interface variable $IV^{Y(LS)=1}$, representing the onset of the limit state LS. The joint probability for parameters $\boldsymbol{\chi}$ of the Log Normal distribution given the sample of structural performance variable values Y can be expressed as the posterior joint probability distribution for the mean and standard deviation for the Normal probability distribution based on a non-informative prior distribution (Box and Tiao, 1992):

$$p\left(\boldsymbol{\chi} \mid \mathbf{Y}\right) = p\left(\mu,\beta \mid \mathbf{Y}\right) = p\left(\mu \mid \beta,\mathbf{Y}\right)\cdot p\left(\beta \mid \mathbf{Y}\right) \tag{5}$$

where $p(\beta|\mathbf{Y})$ is the posterior marginal distribution of β and $p(\mu|\beta,\mathbf{Y})$ is the posterior conditional distribution of μ given β. The marginal PDF for β can be expressed as the $\boldsymbol{\chi}$ distribution:

$$p\left(\beta \mid \mathbf{Y}\right) = k'\cdot \beta^{-N} \cdot e^{-\frac{\upsilon\cdot s^2}{2\cdot\beta^2}} \tag{6}$$

where

$$k' = \left[\frac{1}{2}\cdot\Gamma\left(\frac{\upsilon}{2}\right)\right]^{-1}\cdot\left(\frac{\upsilon\cdot s^2}{2}\right)^{\frac{\upsilon}{2}} \tag{7}$$

The posterior conditional distribution of μ can be calculated as:

$$p\left(\mu \mid \beta,\mathbf{Y}\right) = \sqrt{\frac{N}{2\cdot\pi\cdot\beta^2}}\cdot e^{-\frac{N\cdot\left(\mu-\overline{\ln\mathbf{Y}}\right)^2}{2\cdot\beta^2}} \tag{8}$$

where $\nu=N$-1; $\overline{\ln\mathbf{Y}}$ and s^2 are the (logarithmic) sample average and sample variance of the set of structural performance variable values $\ln(IV^{Y(LS)=1})$ for limit state LS, respectively. The integral in Eq. (3) can be solved numerically by first sampling β based on the PDF in Eq. (6) and then conditioning on the value of sampled β, μ can be sampled based on the PDF in Eq. (8). Conditioning on the sampled pair $\boldsymbol{\chi}=[\mu, \beta]$, the Log Normal analytical fragility curve can be calculated from Eq. (4).

3 NUMERICAL EXAMPLES

As numerical example, two different applications of the Bayesian inference for the assessment of robust fragility in the assessment of vulnerability to natural phenomena such as flooding and earthquake are illustrated.

3.1 Flooding vulnerability

The methodology described in Section 2 for the assessment of robust structural fragility is applied herein in order to estimate the structural fragility curves for flooding for the limit state of collapse for a class of (informal, non-engineered) buildings. The robust fragility is calculated based on small number of (around 20-50) Monte-Carlo simulations. The structural analyses are performed on a bi-dimensional finite-element structural model considering the openings (door and windows). The flood depth h_f measured in meters is taken as the interface variable IV. This is while the performance measure $IV^{Y(LS)=1}$ is taken as the critical flood depth needed for exceeding the collapse limit state for the structure.

3.1.1 Description of the class of structures

The case-study focuses on flood vulnerability assessment for the informal settlements located in the Suna sub ward, shown in Figure 1a, in the Kinondoni District in DSM, Tanzania. Suna, located on the western bank of the Msimbazi river with an extension of about 50 ha, is a historically flood-prone area. The Msimbazi river flows across Dar es Salaam City from the higher areas of Kisarawe in the Coastal region and discharges into the Indian Ocean. Through building-to-building field surveys, it can be established that the portfolio of structures considered belongs to the same class of buildings. This class is consisted of one-storey structures built with cement-stabilized sand bricks (see De Risi et al. 2013b)

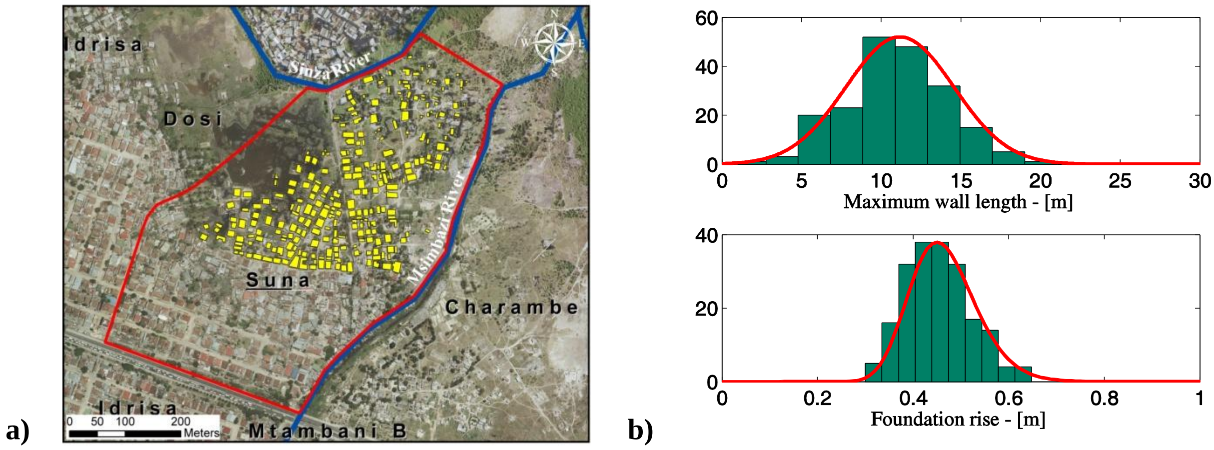


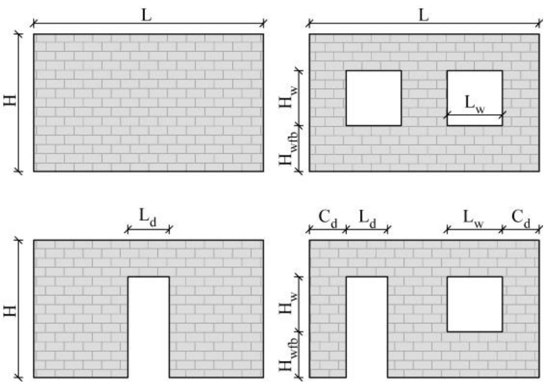
Figure 1 **a)** The case study area and the portfolio of the buildings studied, **b)** Histograms of maximum wall length and platform height.

3.1.2 Characterization of uncertainties

The uncertainties considered are primarily related to building-to-building variability in material properties, geometry and construction details. Orthophoto recognition is used in order to capture the variation of buildings' footprint in the case-study area. Building specific field surveys are used in order to gain better understanding of the geometry and construction details (see for example Figure 1b). Two different types of uncertain variables are taken into account: (1) discrete binary uncertain parameters based on a logic-tree approach; (2) continuous uncertain parameters. Examples of the first type of uncertain parameters considered are, presence of a raised foundation (platform), presence of a barrier, water-tightness of the door, water-tightness of the windows, and visual evidence of degradation in the building. Examples of the second type of uncertain variables are: parameters related to building geometry (see Figure 2), parameters related to the mechanical material properties (e.g., elastic modulus, self weight, etc.) and finally parameters related to structural loading (i.e., the flood velocity/height relationship, see De Risi et al. 2013a).

3.1.3 Structural analysis and loading

The structural model developed herein is consisted of a single panel of elastic shell finite elements modeled using the OpenSees software (McKenna et al., 2006). It is assumed that the panel is clumped (fixed) at the base and hinged at the two sides. The clumped restraint in the base is representative of a good wall-foundation connection; meanwhile, the hinge restraint on the two sides represents a fair transversal connection between two orthogonal walls. Based on the uncertain parameters related to the geometrical properties of the buildings, 4 different types of structural models are generated. These models are distinguished based on the type, number and relative positioning of openings (door and windows). Figure 2 illustrates the various configurations generated in the simulation procedure. As structural loading, hydrostatic loading, hydro-dynamic loading and accidental debris impact are considered. The critical flooding height for the structure is calculated as the flooding height value that can take the structure to the onset of the limit state Y_{LS}=1 based on the weakest link formulation in Equation 2.



L (m) - wall length
H (m) - wall height
t (m) - wall thickness
L_w (m) - window length
H_w (m) - window height
H_{wfb} (m) - window rise
L_d (m) - door length
C_d (m) - corner length
H_f (m) - foundation rise
H_b (m) - barrier height

Figure 2 Four structural configurations considered in the analysis.

3.1.4 Simulation routine

A set of critical height values Y are calculated from standard Monte Carlo simulation with a limited number of samples (N=20). The probability distributions used for generating the Monte Carlo realizations are characterized based on the results of literature survey, orthophoto recognition and building-specific field surveys (see De Risi et al. 2013a for more details).

3.1.5 Results

The two-stage procedure described in Section 2 is used in order to calculate the robust fragility curves for the limit state of collapse based on Equations 3 to 8. In the first stage, a set of N=20 performance variable values Y (i.e., critical flood depth for collapse limit state) are calculated based on small-sample MC simulation. In the second stage, the integral in Equation 3 is approximated numerically through a large-sample Monte Carlo simulation. The light grey lines are the generated fragility curves through this two-stage simulation process.

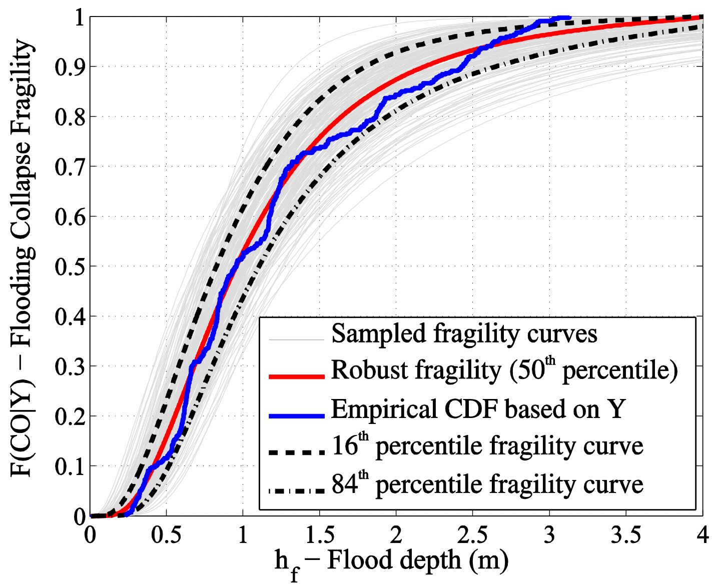


Figure 3 The robust fragility curves (20 simulations) and the empirical fragility curve calculated based on 200 simulations

The fragility curve plotted as a red line in Figure 3 is the 50th percentile of the generated fragility curves. The thick dashed lines are the 16th and the 84th percentiles of the generated fragility curves. The empirical cumulative distribution function for a set of performance variables values Y with *N*=200 is plotted as solid blue line. This is done in order have an idea of the accuracy of the fragility curves calculated based on a small sample of structural performance variable values (*N*=20). It can be observed that in this case the empirical fragility based on 200 MC simulations is well-contained by the 16^{th}-84^{th} percentile fragilities based on 20 simulations (through the two-stage procedure).

3.2 Seismic

One of the most challenging aspects of the seismic assessment of existing buildings is the characterization of structural modeling uncertainties since it measures the incomplete knowledge of the structural properties in as-built conditions. In this regard, it is necessary to account for the uncertainty in construction details (a.k.a. the structural defects), in addition to the uncertainty in the mechanical properties of materials used in construction. Arguably, variations in construction details may affect the component capacities and the eventual governing mechanisms for structural collapse (Jalayer et al., 2011). The two-stage Bayesian method presented in Section 2 is adopted herein for the calculation of robust seismic fragility based on non-linear time-history analyses for an existing RC structure. This is done based on set of *N*=30 structural performance variable values. The first-mode spectral acceleration S_a is used as the interface variable *IV*; the spectral acceleration value that takes the structures closest to the onset of near-collapse limit state $S_a^{Y=1}$ is adopted as the performance variable $IV^{Y=1}$.

3.2.1 Description of the structural model

An existing school structure located in Avellino, Italy is considered for the application of the robust fragility method. The structure is situated in seismic zone II according to the Italian seismic guidelines (OPCM 3431, 2005).

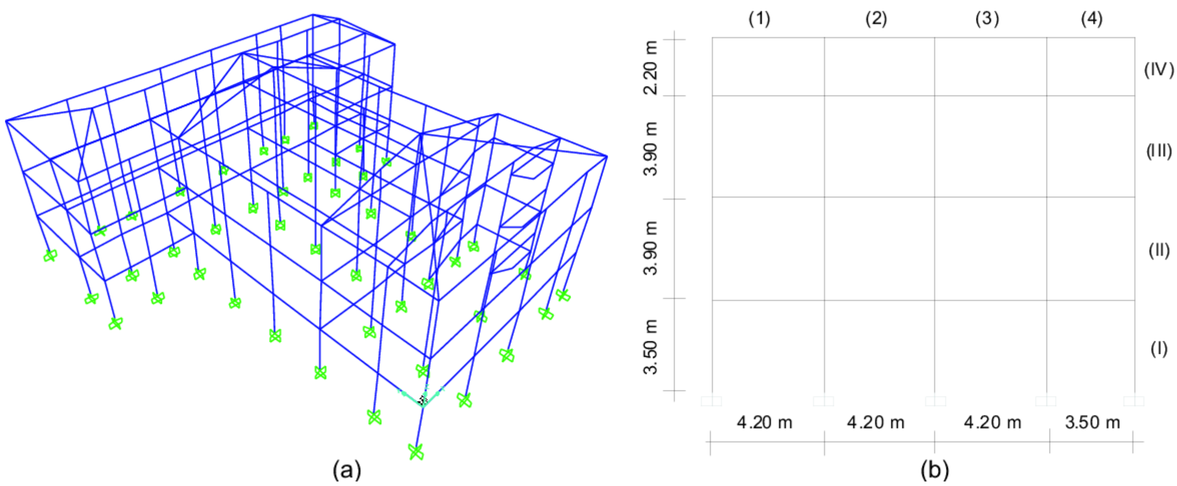


Figure 4. (a) The tri-dimensional view of the scholastic building. (b) The central frame of the case-study building.

The structure is consisted of three stories and a semi-embedded story and its foundation lies on soil type B. For the structure in question, the original design notes and graphics have been gathered. The building is constructed in the 1960's and it is designed for gravity loads only, as it is frequently encountered in the post second world war construction. In Figure 4a, the tri-dimensional view of the structure is illustrated; it can be observed that the building is highly irregular both in plane and elevation. In order to reduce the computational effort, the main central frame in the structure is extracted and used as the structural model (Figure 4b). The columns have rectangular section with the following dimensions: first storey: 40x55cm^2, second storey 40x45cm^2, third storey: 40x40cm^2, and forth storey: 30x40 cm^2. The beams, also with rectangular section, have the following dimensions: 40x70cm^2 at first and second storey, and 30x50cm^2 for the ultimate two floors. The finite element model of the frame is constructed, using the OpenSees software (McKenna et al., 2006), assuming that the non-linear behaviour in the structure is concentrated in plastic hinges.

3.2.2 Structural Analyzes

The multiple-stripes analysis (Jalayer and Cornell, 2009) is used in order to evaluate the spectral acceleration values $S_a^{Y=1}$ for the limit state of near-collapse, based on the cut-set formulation presented in Equation 1. The following mechanisms are considered, the ultimate chord rotation in the components, the formation of global mechanisms (e.g., soft story and beam mechanisms) and the component shear capacity.The structural analyses are performed based on a set of 30 real ground motion records (described in the next sub-section). Three different sets of multiple stripes analyses are performed: (I) considering only the record-to-record variability; (II) considering record-to-record variability and uncertainties related to the material mechanical properties; and (III) considering record-to-record variability, uncertainties related to the material mechanical properties and those related to construction details (a.k.a., structural defects).

3.2.3 Characterization of uncertainties

Three types of uncertainties are considered herein, namely, the uncertainty in the ground motion input, the uncertainty in the material mechanical properties, and the uncertainties in the structural detailing parameters. A set of 30 ground motion records are chosen from the European strong motion database for soil type B ($400 < Vs < 600$ m/s), with moment magnitude between 5.3 to 7.2 and the epicentral distance between 7 and 87 km (see Jalayer et al., 2011). The parameters identifying the probability distributions for the material mechanical properties (concrete strength and the steel yielding force) have been based on the values typical of the post world-war II construction in Italy (Verderame et al. 2001a,b). Table 1 shows the parameters that are used to define the lognormal probability distributions for the material properties.

Table 1. The uncertainties in the material properties.

material	Type	Median	COV
f_c	LN	165	0.15
f_y	LN	3200	0.08

Table 2. The uncertainties in construction details.

Defect	Type	Min	Max
spacing of shear rebar	Uniform (beams)	15cm	30cm
spacing of shear rebar	Uniform (column)	20cm	35cm

In order to characterize the probability distributions for the structural detailing parameters, it is assumed that the information is limited to knowledge of the intervals in which the detailing parameters' value is going to vary. Hence, a uniform distribution is assumed in that interval (Table 2).

3.2.4 The results

Figure 5a illustrates the robust fragility curves calculated through the two-stage approach described in Section 2: case (I) is plotted as solid black line; case (II) is plotted as solid red line; finally case (III) is plotted as solid blue line (note that the results presented fare preliminary and need to be further verified). Figure 5b illustrates the plus/minus one standard deviation band for the fragility curves calculated for the three cases described above. It should be noted that the variance in the fragility estimates is calculated from an alternative approach (with respect to the flooding case-study) by first calculating the expected value of the square of the analytic fragility from a robust formulation analogous to the one expressed in Equation 3. It can be noted taking into account the structural modeling uncertainties leads to a decrease in median capacity (evaluated in terms of $S_a^{Y=1}$) with respect to the case where only record-to-record variability is considered. The significance of considering the uncertainties in the structural defects can be appreciated by comparing the decrease in median capacity with the estimated plus/minus one standard deviation band for the three cases.

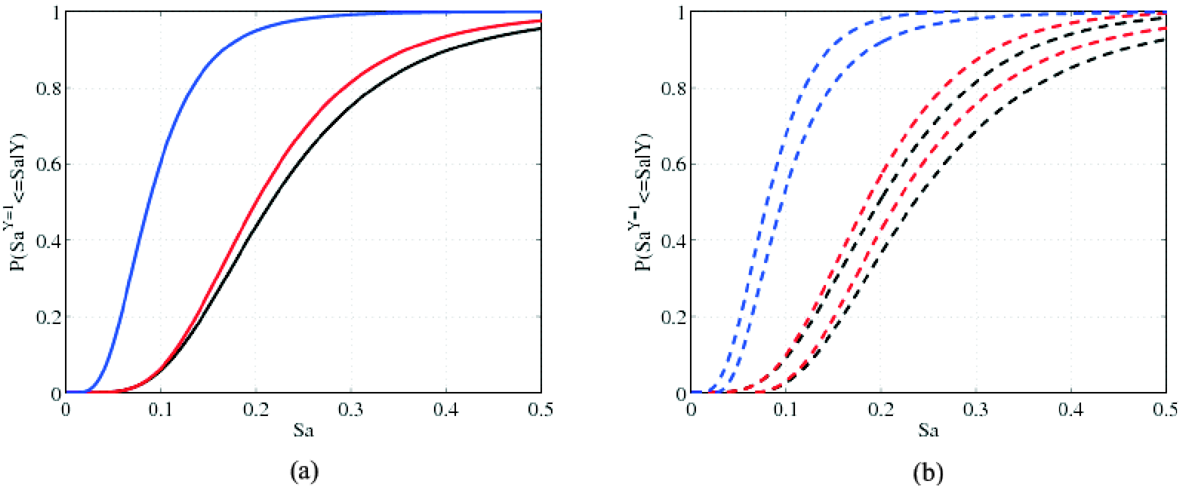


Figure 5. (a) The robust fragility curves for cases (I), (II),(III). (b) Plus/minus one standard deviation bands.

4 CONCLUSIONS

A two-stage Bayesian method for efficient evaluation of structural fragility is presented. In the first stage, this method uses a small set (N=10-50) of structural performance variable values as data in order to construct probability distributions for parameters of a prescribed analytic fragility model. In the second stage, large-sample MC simulations are used in order to calculate the percentile statistics of the fragility curve (coined also as the robust fragility curves). The application of this methodology is illustrated for flood vulnerability assessment for a class of non-engineered buildings and seismic vulnerability assessment for an existing RC building. In the flood vulnerability assessment example, the robust fragility curves obtained based N=20 structural analyses are compared with MC simulation based N=200 structural analyses. In the seismic vulnerability assessment case, it is demonstrated how this two-stage method can be used based on structural performance variables calculated for a selection of recorded ground motions. The influence of considering the uncertainties in construction details (defects) on the robust fragility curve seems to be significant.

ACKNOWLEDGEMENTS

This work was supported in part by the European Commission's seventh framework program Climate Change and Urban Vulnerability in Africa (CLUVA), FP7-ENV-2010, Grant No. 265137 and the project ReLUIS 2005/2008 – Dipartimento della Protezione Civile. This support is gratefully acknowledged. The authors would like to make a special acknowledgement to Elinorata Mbuya and Prof. Alphonce Kyessi of the Institute of Human Settlement Studies, ARDHI University, Dar Es Salaam Tanzania, for providing the building-specific survey results.

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