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Probability models to assess the seismic safety of rigid block-like structures and the effectiveness of two safety devices

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Abstract

When subject to earthquakes, some objects and structures, such as statues, obelisks, storage systems, and transformers, show a dynamic behavior that can be modeled considering the object/structure as a rigid block. Several papers have studied the dynamic behavior of both stand-alone rigid blocks and systems where rigid blocks have been paired with safety devices to prevent or delay the overturning of the blocks. Although the safety devices have generally been proven to be effective, their effectiveness changes substantially varying the parameters that characterize the system and the seismic input. This paper compares the seismic responses of stand along rigid blocks with those of blocks coupled with two candidate safety devices: an isolating base and a pendulum mass damper. To account for the relevant uncertainties, probabilistic seismic demand models are developed using a Bayesian approach. The probabilistic models are then used along with the overturning capacities of the blocks to construct fragility curves that give a prediction of the probability of overturning occurrence as a function of some characteristics of the blocks, of the safety devices, as well as of the seismic excitation, i.e. the slenderness of the body and the peak ground acceleration. The data needed to develop the probabilistic model are obtained integrating the nonlinear equations of motion of the two systems subject to selected ground motions. In the end, some numerical examples are proposed.

Keywords: Rigid block; probabilistic models; failure probability; logistic regression.

1. Introduction

The dynamic behavior under seismic excitation exhibited by rigid block-like elements, such as statues, obelisks, storage systems, transformers and generally slender objects that are not anchored to the ground, can be approximated considering rigid block models [1, 3, 4, 9]. Previous papers analyzed the seismic response of systems constituted by

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one or more rigid blocks [12, 16]. To prevent or delay the overturn of this rigid block-like elements, some researchers considered adding some safety devices. Beside base isolation [4] with and without security stops, also tuned mass dampers [11] and pendulum mass dampers [3] have been proposed to improve the dynamic behavior of rigid blocks. Although the majority of the papers deals with passive control systems, some researchers suggested the use of active control systems [2]. In most real cases the choice of the safety system to be used is constrained by the nature and characteristics of the rigid block-like element that has to be protected. Assuming that this choice is only aimed to obtain the best seismic performance, since the effectiveness of each safety system depends on the characteristics of the rigid block, it is not possible to determine a priori which device will result in the best performance. One possibility is to use probabilistic seismic demand models as in [1] and [8] dependent on the characteristics of the rigid block, of the isolating device and the ground motion.

This paper compares the seismic performance of three systems: stand-alone rigid blocks, rigid blocks with pendulum mass damper and rigid blocks with base isolation. A probabilistic seismic demand model is constructed for each system to estimate the maximum angle of rotation for the blocks. The models are developed by logistic regression. The data used to model the probabilistic seismic demand models are obtained via direct integration of the equations of motion of the three systems presented in [4] and [3]. The characteristics of the rigid blocks and the safety devices are chosen using the experimental design methodology proposed in [15]. A large set of ground motion records is used to take into account earthquakes with different characteristics.

2. Failure mechanisms

For rigid block-like elements, and especially for the slenderer ones, the most common failure mechanism is overturning. Other failure mechanisms include the impact against surrounding objects and the fall from the support if the element is positioned on a base. In the majority of real cases, however, the horizontal movement is prevented by either a high friction coefficient between element and support or the existence of specific restraints. We assume that the body is prevented from moving horizontally and consequently the overturn is the only possible failure mechanism. The overturning occurrence is typically described as the rotation angle ϑ (angle between the base of the block element and either the ground or the isolating base) exceeding a critical angle defined by the geometry of the block [1, 16]. In our case, to account for the dynamic effects that may restore the block-like element in a safe position, we consider that the element overturns when $\vartheta = \pi / 2$.

3. Failure probability estimation

The overturning occurrence is modeled as a categorical response variable $y = \{0,1\}$, where y=1 if the rigid body overturns and 0 otherwise. The overturn probability P[y=1] = p is described with a logistic regression model as

$$\operatorname{logit}\left(p(\boldsymbol{\theta},\mathbf{x},\mathbf{S})\right) = \ln\left(\frac{p(\boldsymbol{\theta},\mathbf{x},\mathbf{S})}{1-p(\boldsymbol{\theta},\mathbf{x},\mathbf{S})}\right) = \theta_0 + \theta_1 h_1(\mathbf{x},\mathbf{S}) + \ldots + \theta_n h_n(\mathbf{x},\mathbf{S}) \quad (1)$$

Terms h_i define a set of explanatory functions (for i=1…n) of the regressors. The regressors may be geometrical and mechanical characteristic of the system, **x**, and earthquake characteristics, **S**. The model parameters $\boldsymbol{\theta} = \{\theta_0 \ldots \theta_n\}$ are unknown and may be estimated with different approaches such as Maximum Likelihood estimation or Bayesian estimation. This kind of model has the advantages to be robust to noise, and efficient for large amounts of data. Moreover, it is can be used as baseline for more complex approaches.

4. Bayesian parameter estimation and model selection

The distributions of the model parameters $\boldsymbol{\theta}$ are obtained by a Bayesian estimation because the regressors are not categorical functions and consequently there is no closed form solution for the logistic regression. With this approach, the posterior distribution of the parameters $f''(\boldsymbol{\theta})$ can be obtained as

$$f''(\boldsymbol{\theta}) = wL(\boldsymbol{\theta}) f'(\boldsymbol{\theta}) \quad (2)$$

In Eq. 2, $f'(\boldsymbol{\theta})$ is the prior distribution, $L(\boldsymbol{\theta})$ is the Likelihood function and $w = \left[\int L(\boldsymbol{\theta}) f'(\boldsymbol{\theta}) \mathrm{d}\boldsymbol{\theta}\right]^{-1}$ is a normalizing constant. For the prior distribution $f'(\boldsymbol{\theta})$, assuming the independence of the parameters $\boldsymbol{\theta}$, a uniform distribution **U**(a, b) is chosen as diffuse prior. For independent observations of overturning occurrences, the likelihood function is defined as

$$L(\boldsymbol{\theta}) = \prod_{j=1}^{m} \left[p_j^{y_j} \cdot (1 - p_j)^{1-y_j} \right] \quad (3)$$

where n is the number of available observations; and p_j is the probability of the j^{th} outcome of overturning observation, y_j. Using as point estimate of the parameters the mode of the posterior distribution, the obtained estimator $\tilde{\boldsymbol{\theta}}$ is the same that would be found using the Maximum Likelihood estimation. After computing the posterior statistics of the model parameters, the explanatory functions associated with the parameters with the largest coefficient of variations can be dropped from the model in a stepwise fashion. The details of these stepwise deletion procedure can be found in [5, 6].

5. Virtual data for model calibration

5.1. Physical systems

The three systems considered in the numerical simulations are constituted by the same rigid block of dimensions $1 \times 2b \times 2h\ m^3$ and mass density $\rho = 1800\, kg / m^3$ shown in Figure 1. The first system is the stand-alone rigid block (Figure1a). In the second system, the rigid block is placed on an oscillating base connected to the ground by a viscoelastic device with damping coefficient c and stiffness k (Figure1b). In the third system, the block is coupled with a pendulum of length l and mass m, acting as a mass damper (Figure1c). Although all the considered models of rigid block-like elements used in this study [3,4] can take into account the eccentricity of the center of mass of the rigid block, this study is focused on symmetric rigid blocks. For each system, the dynamics is described by a set of equations of motion and a set of equations that define the impact of the rigid block and either its support (in the base isolation case) or the ground (for the others two models). These equations can be found in [4] for the stand-alone and the base isolated rigid block-like elements and in [3] for the block-pendulum system.

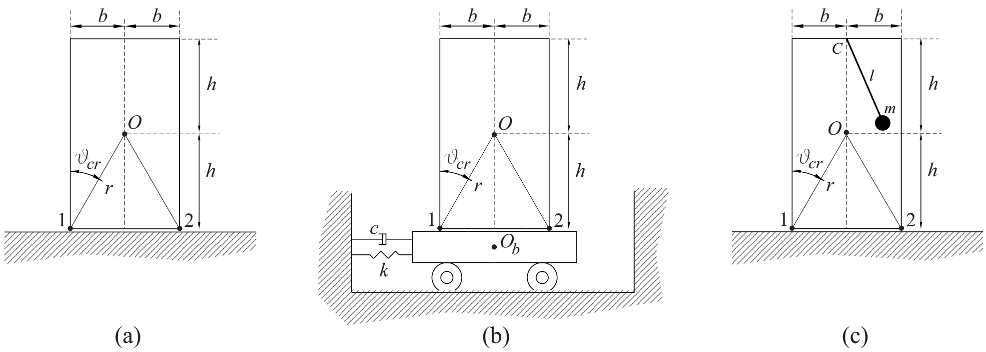

Fig. 1. (a) stand-alone rigid block; (b) rigid block on an oscillating base; (c) rigid block with pendulum mass damper.

5.2. Ground motion selection and simulation design

To investigate the entire space of the design variables with the minimum number of time history analysis, this paper uses two different methods for the choice of the design variable related to the physical systems and the ground motions.

Different realizations of the mechanical systems are sampled with a version of the Latin Hypercube Sampling (LHS) technique with control on the samples' correlation [14, 15]. This procedure uses the simulated annealing method to solve the problem of optimal sample ordering. The output consists of realistic system configurations where the design variables respect the prescribed correlations and, at the same time, the introduction of spurious correlations is prevented. This study is focused on only three design variables for the systems. Two are related to the rigid block: the width of its base b and its slenderness λ. The third is the characteristic period of the safety device T (for the pendulum it is the period obtained from the linearized equation of motion.) The distributions of these three design variable are assumed to be uniform within assigned ranges. The range of values for the base of the block, $2b$, goes from 0.40 *m* to 0.80 *m* while the slenderness λ, varies between 3 and 7. It is assumed that the safety devices are designed to have a characteristic period between 0.5 *s* and 3.0 *s*. The sampling process leads to 60 different configurations for the three systems, all of which are coupled with all the selected ground motions.

The ground motion selection is based on the bin approach [7, 10, 13]. This method allows to include in the analyses both the effects of the ground motions and the site condition. For the present study, ground motions are sorted in two site classes representing rock and soil sites. Each class includes five bins that are the same as in [13]. To the first four bins (Bins 1-4) belong ground motions with specific combinations of moment magnitude M and site-to-source distance R (Bin 1 with M=6 and R=10*Km*, Bin 2 with M=6 and R=25*Km*, Bin 3 with M=7 and R=10*Km* and Bin 4 with M=7 and R=25*Km*). Instead, to take into account sites that experience rupture directivity effects, a 5th bin (Bin 5) containing 20 unscaled near-fault ground motions characterized by strong velocity pulses of varying periods in their strike-normal components are considered. In the analyses, five ground motions are randomly selected from each bin for a total of 50 ground motions. The combination of ground motion selection and simulation design produces a total of 9,000 simulations whose output are used for the failure probability estimation.

6. Results

For a preliminary analysis, the explanatory functions chosen are the three design variables that describe the system (the length of the base $2b$, the slenderness λ, and the characteristic period T), peak ground acceleration PGA and a measure of the spectral content of the registered earthquake Sa (evaluated as the integral of the acceleration spectrum between T=0*s* and T=3*s*). Therefore, the overturning probability can be expressed as

$$p(\boldsymbol{\theta},\mathbf{x},\mathbf{S})=\frac{\exp\left[\theta_0+\theta_1\lambda+2\theta_2 b+\theta_3 T+\theta_4 PGA+\theta_5 Sa\right]}{1+\exp\left[\theta_0+\theta_1\lambda+2\theta_2 b+\theta_3 T+\theta_4 PGA+\theta_5 Sa\right]} \tag{4}$$

Given the high number of samples, we can expect the distribution of the model parameters to be $\mathrm{N}(\boldsymbol{\mu}'',\boldsymbol{\Sigma}_{\boldsymbol{\theta\theta}})$,

$$\boldsymbol{\theta}\sim\mathrm{N}(\boldsymbol{\mu}'',\boldsymbol{\Sigma}_{\boldsymbol{\theta\theta}}) \tag{5}$$

where the posterior mean, $\boldsymbol{\mu}''$, and covariance matrix, $\boldsymbol{\Sigma}_{\boldsymbol{\theta\theta}}$, (Table 1) are obtained using the approach described in Section 4.

Table 1. Estimates of the posterior mean and variance of the model parameters

		θ_0	θ_1	θ_2	θ_3	θ_4	θ_5
Stand-alone block	$\mathrm{E}[\theta_i]=\mu_i''$	−15.019	0.359	−6.586	1.547	2.268	2.099
	$\mathrm{Var}[\theta_i]$	0.592	0.363	29.894	4.860	0.012	0.010
Isolated block	$\mathrm{E}[\theta_i]=\mu_i''$	−10.146	0.417	−1.750	−1.117	1.693	1.718
	$\mathrm{Var}[\theta_{ib,i}]$	0.440	0.004	0.400	0.012	0.006	0.007
	$\mathrm{E}[\theta_{db,i}]=\mu_{db,i}''$	−12.213	−0.725	−3.395	−0.163	−1.837	1.794

Block with mass damper	$\text{Var}\left[\theta_{db,i}\right]$	0.458	0.004	0.330	0.008	0.007	0.007

For the three systems, the correlation matrices are (presented counter-clock wise for stand-alone block, isolated block, and block with mass damper)

$$\mathbf{R_{00}} = \begin{bmatrix} 1 & -0.051 & -0.009 & 0.025 & -0.725 & -0.747 \\ & 1 & 0.986 & -0.994 & 0.015 & 0.003 \\ & & 1 & -0.994 & -0.039 & -0.055 \\ & & & 1 & -0.024 & 0.039 \\ & Sym & & & 1 & 0.769 \\ & & & & & 1 \end{bmatrix};$$
$$\mathbf{R_{00}} = \begin{bmatrix} 1 & -0.626 & -0.521 & 0.002 & -0.521 & -0.571 \\ & 1 & 0.017 & -0.084 & 0.208 & 0.207 \\ & & 1 & 0.033 & -0.089 & -0.085 \\ & & & 1 & -0.344 & -0.330 \\ & Sym & & & 1 & 0.654 \\ & & & & & 1 \end{bmatrix}; \mathbf{R_{00}} = \begin{bmatrix} 1 & -0.685 & -0.348 & -0.208 & -0.623 & -0.657 \\ & 1 & -0.072 & 0.019 & 0.325 & 0.340 \\ & & 1 & -0.002 & -0.117 & -0.172 \\ & & & 1 & -0.044 & -0.046 \\ & Sym & & & 1 & 0.696 \\ & & & & & 1 \end{bmatrix}; \quad (6)$$

To compare the behavior of three different systems, it is possible to compare the corresponding probabilities of failure P_f conditioned on one or more explanatory function. Figures 2a and 2b show the fragilities obtained using PGA as intensity measures. The solid blue line refers to the stand-alone block, the pointed red one to the isolated block and the dashed black line to the damped block. The difference between the systems in Figures 2a and 2b is the length of the base 2b, which is equal to 0.4 m for the systems in Figure 2a and 0.6 m for the systems in Figure 2b. The other parameters are kept constant in the two case, T=2s, $\lambda = 2$, and Sa=3.7.

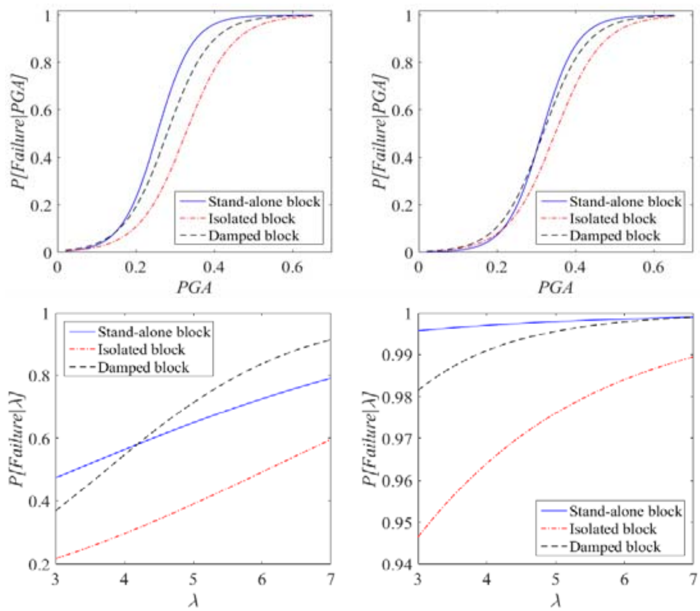

Figure 2. Probability of failure of a block-like elements conditioned on PGA and λ.

As it is possible to see, for the two cases shown, the system with base isolation is the least probable to overturn, except in a small range of low PGAs in the case with a larger base. Moreover, in this latter case, the pendulum mass damper seems to be effective only for higher values of *PGA*. Similar comparisons can be made by varying the mechanic characteristics of the systems. Figures 2c and 2d show the probability of failure for systems under excitations with different *PGA*s, *PGA*=0.25g for Figure 2c and *PGA*=0.5g for Figure 2d. The other parameters are kept constant in the two case, *T*=2*s*, 2*b*=0.4*m*, and *Sa*=3.7. Also in this case, while the system with base isolation seems to have a safer behavior in all the range of slenderness considered in the analysis, the rigid block-like element with pendulum mass damper has a lower probability of failure compared to the stand alone block only as the slenderness of the block increases.

7. Conclusions

The presented research proposes seismic probability models that can be used to compare the effectiveness of base isolation and tuned mass damper as safety devices for rocking rigid block-like elements. For the unprotected and the protected block, the probability of failure is obtained with a logistic regression on mechanical characteristics (the length of the base, *2b,* the slenderness, λ and the characteristic period, *T*) and earthquake characteristics (the peak ground acceleration, *PGA*, and a measure proportional to the spectral acceleration, *Sa*). This kind of model provides a handy tool to help the preliminary design of protection devices for rigid block–like elements focused on the overturning occurrence and not on the description of the motion. The authors use the simulated annealing technique to reduce the number of simulation needed to identify the parameters of the models and follow the bin approach for the choice of the seismic input. As most probabilistic models, their use should be limited to elements whose characteristics fall within the ranges of values used in the simulations.

Although a larger number of analyses is needed to fully characterize the behavior of the two system with protective devices, preliminary results show that the effectiveness of both base isolation and pendulum mass damper vary along the range of the mechanical parameters. However, base isolation seems more efficient, especially for lower PGAs and less slender bodies.

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