Probabilistic Models for Uncertainty Quantification of Soil Properties on Site Response Analysis

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Abstract: The geotechnical properties of soil deposit and the variability associated with their probable distributions have a profound impact on the seismic response of a site. In the present work, the influences of soil profile characterizations corresponding to the shear wave velocity (V_s), density, and material degradation using various probabilistic distributions are investigated. A stochastic process is introduced for solving the spatial variability in soil deposit via Monte Carlo simulations. The results are validated with those obtained from the reference solution using the Strata program version 0.5.5. Additionally, sensitivity analysis is conducted to investigate the effect of the random input variables in the soil profile. The analysis concludes that the consideration of probabilistic distributions of the geotechnical parameters plays a significant role in evaluating the reliability of a site. The variability in material degradation has a greater impact than the unit weight on site response. Furthermore, comparatively the variability in V_s for both the Toro model and log-normal distribution is identical for periods greater than 1.0 s, while in the range of lower periods, the former is lower than the latter with maximum reductions of 11.14% and 20.86% in surface response spectra and amplification factor, respectively. **DOI: 10.1061/AJRUA6.0001079.** *© 2020 American Society of Civil Engineers.*

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Introduction

Predicting the dynamic behavior of local soil is an essential aspect of seismic risk assessment that can be calculated through site response analysis (SRA) (Kramer 1996). In previous studies, several methods for analyzing the ground response have been proposed, including one-dimensional (1D) SRA (Hashash 2012; Idriss and Sun 1993; Kim et al. 2016; Kottke and Rathje 2008), two-dimensional (2D) SRA (Hudson et al. 1994), and finite element programs (McKenna 2011). One-dimensional ground response analysis is performed using a frequency-domain equivalent-linear (EQL) method (Idriss and Seed 1968; Idriss and Sun 1993; Schnabel et al. 1972) and a time-domain nonlinear (NL) method (Hashash 2012). The EQL approach has been widely used due to its simplicity (Du et al. 2018; Du and Pan 2016; Kaklamanos et al. 2013; Tran et al. 2018). This approach was first proposed by Idriss and Seed (1968) and was adopted in the SHAKE program by Schnabel et al. (1972). Later, the program was modified to SHAKE91 by Idriss and Sun (1993).

In the practical earthquake engineering applications for structures [i.e., buildings, foundations, nuclear power plants (NPPs), etc.], it is necessary to perform ground response analysis in order to predict the adequate seismic response (Cao et al. 2019; Nguyen and Kim 2017; Nguyen et al. 2020; Salman et al. 2020). The variabilities in the soil profile are the primary parameters that must be considered for a sophisticated solution due to their effect on the site response. Therefore, it is required to develop a simulation technique that accounts for the effects of uncertainty of random input variables on the seismic response. The stochastic model is capable of solving a large number of simulations, and the selection of probability distribution functions representing the variation of input variables is an important part for statistical analysis (Bazzurro and Cornell 2004; Darendeli 2001; Rota et al. 2011; Toro 1996; Tran and Kim 2019; Wang et al. 2018, 2015). For example, Wang et al. (2015) studied a statistic concept called the mixture model and the Bayes' theorem to obtain the site-specific probability distribution of soil properties. Toro (1996) developed a statistical model to randomize the layering and shear wave velocity (V_s), where the uncertainty of V_s was described as the log-normal distribution. Rota et al. (2011) proposed a fully probabilistic process that considers the variability in input ground motions and dynamic soil properties for a site in central Italy. In addition, Bazzurro and Cornell (2004) performed Monte Carlo simulations (MCS) for the uncertainty of soil properties to evaluate the amplification between the ground shaking and the bedrock motion. In another study, an empirical model was proposed by Darendeli (2001) for investigating the variability of nonlinear properties. However, to the best knowledge of the authors, no studies on the influence of probabilistic variations in site characteristics on the stochastic site response analysis have been reported in the published literature. Thus, the challenge is how to consider this effect on the generation of soil profiles.

Based on the above literature surveys, this study aims to investigate the effect of different probabilistic distributions of geotechnical parameters of a soil deposit. The numerical simulation is

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Table 1. Geotechnical properties of the site

Layer	Thickness (m)	V_s (m/s)	Unit weight (kN/m^3)	σ'_0 (atm[a])	OCR	PI
Layer 1	6	250	18	0.36	1.0	10
Layer 2	25	300	18	2.2	1.0	10
Layer 3	30	460	19	5.6	1.0	10
Layer 4	30	700	22	7.7	1.0	10

[a]atm = standard atmosphere pressure unit.

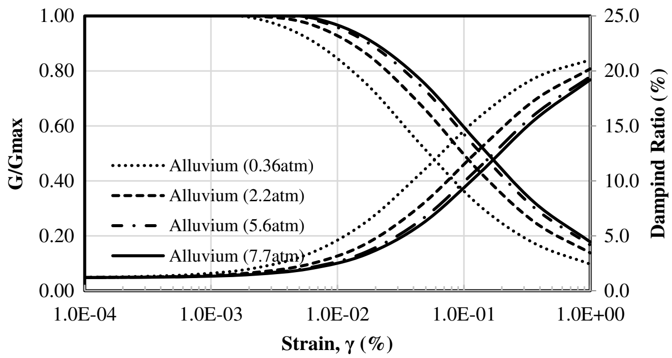

Fig. 1. Nonlinear modulus reduction and damping for soil.

conducted for a deep alluvium site, which is situated within the Transverse Ranges structural province of Southern California (Gibbs et al. 1996). Several random variables such as V_s, density (γ), and material degradation (Aladejare and Wang 2017) were considered. Uncertainties of these variables are applied in the stochastic analysis for predicting the response of the site. A computer program for a probabilistic site response analysis, PSHAKE, is developed based on the original SHAKE91 framework for solving the variabilities in soil characterizations with different probability distributions via MCS. The variable randomizations include the variations of (1) V_s using the normal or log-normal distribution, (2) V_s using the Toro model, (3) unit weight, and (4) dynamic soil properties based on the Darendeli model. To verify the accuracy of the proposed solution, the V_S uncertainty using the Toro model is carried out. Results in peak ground acceleration (PGA), maximum shear strain, surface response spectra (Sa_s), and amplification function (AF) are compared with the reference solution of Strata software developed by Kottke and Rathje (2008). Furthermore, the effects of different input parameters of soil properties are carried out using sensitivity analysis.

Site Description and Input Motion

Geotechnical and Geophysical Parameters of Site

Soil properties are natural parameters of geomaterials and vary from site to site (Wang et al. 2016); thus, determining these parameters plays a significant role in geotechnical analyses and designs. In this research, the specific site located in the San Fernando Valley of Southern California, namely, Sylmar County Hospital (SCH) (Gibbs et al. 1996), is selected for site response analysis. The properties of the site for each layer are summarized in Table 1. The soil medium has about 90 m alluvium soil above bedrock, with shear wave velocities of 250 m/s at the surface and 700 m/s at 60 m depth.

Shear modulus degradation and damping (MRD) are also key parameters in calculating the ground response. The variation of shear modulus with shear strain of soil is described by shear modulus reduction, while the variation of damping with shear strain is defined by the damping curve. It is worth mentioning that the characteristics of nonlinear soil properties are complex; thus, in this study, the soil material model proposed by Darendeli (2001) is applied for each layer. The parameter for this model is defined as a function of mean effective stress (σ'_0), overconsolidation ratio (OCR), and plasticity index (PI), in which σ'_0 is used to consider the variability in the MRD curves with its values ranging from 0.36 to 7.7 atm (Table 1). Fig. 1 shows the predicted MRD curves of the site with values of 10 and 1 Hz for the number of cycles and excitation frequency, respectively.

Seismic Input

In this research, the time history recorded on January 17th of 1994 during the Northridge earthquake at the Arleta Nordhoff fire station is used for performing the site response analysis. The signal is obtained from the Pacific Earthquake Engineering Research Center (PEER) Ground Motion Database (Ancheta et al. 2012). The PGA and time interval of the input motion are 0.35 g and 0.02 s, respectively, and it is applied at the bedrock of the numerical model. This seismic input is representative of strong motion registered for a station close to the seismic source (distance to the fault is 3.9 km), and it is commonly used in many studies (Gibbs et al. 1996; Hussan et al. 2018; Nguyen et al. 2014; Tran and Kim 2019). Fig. 2 represents the time history of ground motion and the resulting response spectral in this analysis.

Variability in the Soil Profile

Uncertainty in the soil properties for the ground response analysis can be effectively randomized using Monte Carlo simulation.

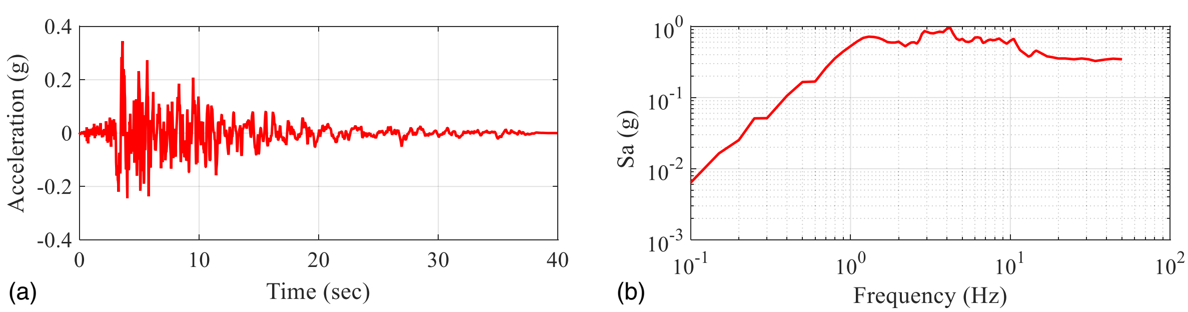

Fig. 2. Earthquake record: (a) time history of motion; and (b) response spectra.

The relevant input parameters such as V_s, γ, and MRD are most effective for evaluating the response of the specific site. In practice, it is difficult to model and estimate the variability of geotechnical properties of a site with a probabilistic distribution. Thus, this research aims to address this challenge using the stochastic concept under various uncertain cases. Four cases based on the variability of geometrical properties are addressed that include variations in the following: V_S using a log-normal distribution (Case 1), V_S using the Toro model (Case 2), unit weight (Case 3), and dynamic soil properties using the Darendeli model (Case 4). The detailed simulations for each case are described as follows.

Spatially Varied Shear Wave Velocity Profiles–Toro Model (Case 1)

Toro (1995) developed a probabilistic model for shear wave velocity profiles based on the design guideline provided by EPRI (1993). This model is used to simulate the artificial soil profile, and it consists of two separate parts. The first one is a layering model that captures the variability in layer thickness. The second part is for the V_s associated with each layer, called a velocity model.

In this study, the randomized V_s profiles are generated from the Toro model, which is described as a log-normal distribution with the median of V_s, $\ln(V_{median,i})$, and the standard deviation of V_s, $\sigma_{\ln V}$. The shear wave velocity of layer i, (V_i), can be expressed as

$$V_i = \exp\left[Z_i \cdot \sigma_{\ln V_S} + \ln(V_{median,i})\right] \tag{1}$$

where Z_i = random standard normal variable for layer i:

$$Z_i = \begin{cases} \varepsilon_1, & \text{for the surface layer} \\ \rho Z_{i-1} + \varepsilon_i\sqrt{1-\rho^2}, & \text{for other layers} \end{cases} \tag{2}$$

where Z_{i-1} = standard normal variable of the previous layer; and ε_1 = independent normal random variable with zero mean and unit standard deviation. The ρ in Eq. (2) can be defined as

$$\rho(d,h) = [1-\rho_d(d)]\rho_h(h) + \rho_d(d) \tag{3}$$

where ρ_h and ρ_d represent the thickness-dependent and depth-dependent correlations, and they are expressed as a function of thickness (h) and depth (d), respectively:

$$\rho_h(h) = \rho_0 e^{(-h/\Delta)} \tag{4}$$

$$\rho_d(d) = \begin{cases} \rho_{200}\left(\dfrac{d+d_0}{200+d_0}\right)^b, & d \le 200 \\ \rho_{200}, & d > 200 \end{cases} \tag{5}$$

where $\rho_0, \rho_{200}, d_0, b$, and Δ = fitting factors of the model.

Log-Normal Distribution (Case 2)

The log-normal distribution is widely used to model the physical values of engineering phenomena (Kim 2017). The uncertainty of V_s with the standard deviation $\sigma_{\ln V_s}$ is calculated using the relationship between the log-normal function (Benjamin and Cornell 2014; Kim 2017) as follows:

$$\sigma_{\ln V_S} = \sqrt{\ln\left(\mathrm{COV}_{V_S}^2 + 1\right)} \tag{6}$$

where $\mathrm{COV}_{V_S} = \frac{\sigma_{V_S}}{\mu_{V_S}} = \sqrt{\exp(\sigma_{\ln V_S}^2) - 1}$ is the coefficient of variation (COV) of V_s and μ_{V_S} = mean of V_s.

Simulation of Density Variability (Case 3)

Similar to Case 2, the variability in density is also simulated using the log-normal approach. Therefore, following Kim (2017), the distribution of unit weight is expressed using Eq. (6).

Generated Nonlinear Soil Properties (Case 4)

According to Darendeli (2001), the uncertainty in MRD is modeled as a normal distribution. The random variable $G/G_{\max}$ and D are produced from the baseline (mean) values ($[G/G_{\max}(\gamma)]_{mean}$ and $[D(\gamma)]_{mean}$) corresponding to uncorrelated random variables (ε_1 and ε_2) with zero mean and unit standard deviation, respectively. The $G/G_{\max}$ and D values are computed from Eqs. (7) and (8)

$$G/G_{\max}(\gamma) = [G/G_{\max}(\gamma)]_{mean} + \varepsilon_1\sigma_{NG} \tag{7}$$

$$D(\gamma) = [D(\gamma)]_{mean} + \rho\sigma_D\varepsilon_1 + \sigma_D\sqrt{1-\rho^2}\varepsilon_2 \tag{8}$$

where σ_{NG} and σ_D = standard deviations of the normalized shear modulus and damping ratio, respectively, and they are given as follows:

$$\sigma_{NG} = \exp(-4.23) + \sqrt{\frac{0.25}{\exp(3.62)} - \frac{(\frac{G}{G_{\max}} - 0.5)^2}{\exp(3.62)}} \tag{9}$$

$$\sigma_D = \exp(-5.0) + \exp(-0.25)\sqrt{D(\%)} \tag{10}$$

Based on the previous discussions, the different models for randomizations are graphically illustrated in Fig. 3. Note that in the first two cases, the randomizations of the shear wave velocity are considered with different approaches, and the results in which the COV of 0.3 is assumed to be the same are then compared.

Framework of Stochastic Site Response Analysis

Methodology

The stochastic site response analysis is conducted for a site due to seismic loading based on the MCS that is adopted for the models with a large number of aleatory variables (Baecher and Christian 2005). Fig. 4 shows the schematic description of the process with the MCS module. The MCS module repeats the subprocess for each simulation and conducts statistical analysis (i.e., mean values and standard deviations). The computer program written in Python programming, PSHAKE, has been developed based on the aforementioned stochastic process (Tran et al. 2020). The solution can consider the uncertainties of geotechnical parameters such as V_s, layer thickness, unit weight, and material degradation. This methodology proceeds as follows:

1. Determine the statistical properties for the various parameters;
2. Generate the input variables;
3. Conducte the ground response analysis for each simulation and record the response; and
4. Statistical analysis of the results.

The parameters required for the program consist of the acceleration data and the control input file (e.g., control.inp). In the control file, the COV parameter is defined to consider the variation of the soil profile. The response parameters, including peak ground motion profile, maximum shear strain profile, surface response spectra, and amplification factors, are considered for the statistical analysis.

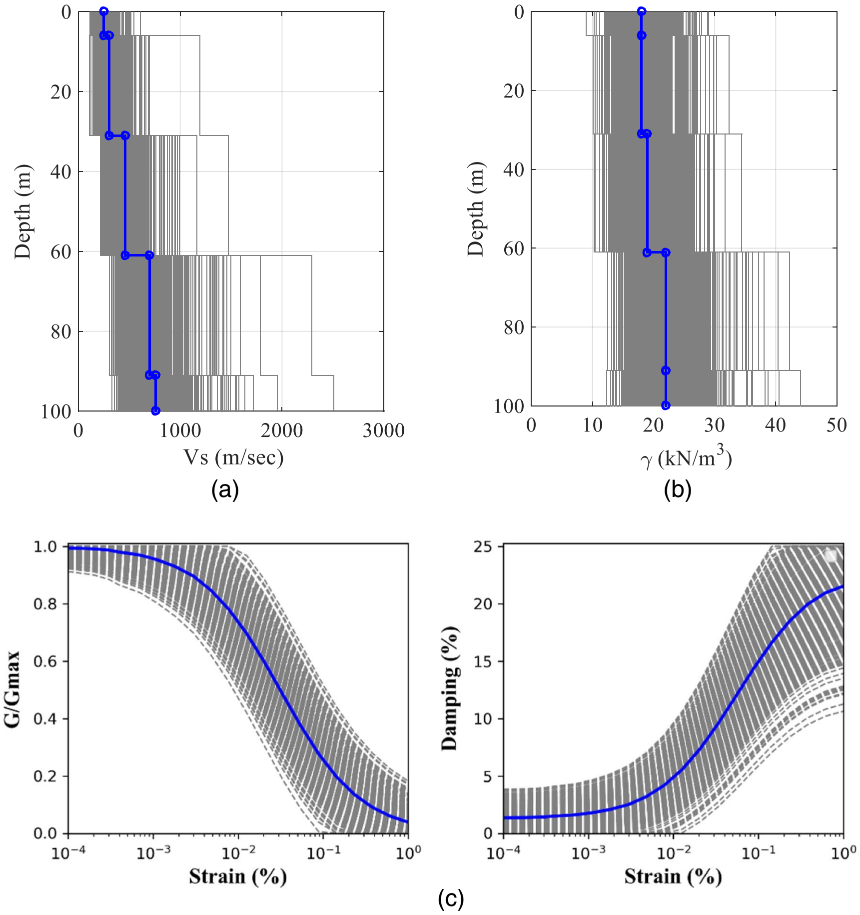

Fig. 3. Graphical representation of the variability of (a) shear wave velocity; (b) unit weight; and (c) nonlinear property curves.

Verification of the Proposed Process

The seismic response of the soil is sensitive to the variability in the soil profile. It is important to validate these properties of the soil deposit for sophisticated analysis. For verification purposes, the randomization of shear wave velocity following the Toro model is performed. The COV of 0.317 is used to consider the spatial variability of the soil profile. To verify the accuracy of the proposed program, a comparative solution is presented between this study and the Strata program based on (1) the PGA and maximum shear strain in the soil profile and (2) the surface response spectra, Sa_s, and amplification factor, AF, for the soil profile.

Fig. 5 displays the comparison of the PGA and maximum shear strain profile obtained from PSHAKE and Strata. A comparison of the mean values with the varying depth of the soil profile is enlisted in Table 2 with the maximum difference of 5.86% and 9.70% for PGA and maximum shear strain profiles, respectively. Based on the analysis, the difference between the two methods is comparable. This concludes that the proposed program has a good agreement with the reference solution.

In site response analysis, the amplification function is used to determine the amplification effect induced by the ground motion. The AF is defined as the ratio between response spectra at the soil surface to the bedrock (Barani et al. 2013). The AF is expressed as

$$AF(T) = \frac{Sa_s(T)}{Sa_r(T)} \tag{11}$$

where $Sa_s(T)$ and $Sa_r(T)$ = acceleration response spectrum of motions at the surface and at the bedrock, respectively.

In Fig. 6, the Sa_s and AF of both PSHAKE and Strata are presented. The agreement in the dynamic response parameters manifests that results recorded from the proposed analysis and the reference solution are consistent.

Sensitivity Analysis

To evaluate the effect of soil characteristics on the stochastic site response analysis, the sensitivity analysis is performed by randomizing one parameter and keeping the others constant. A total of 500 simulations for each case described in the "Variability in the Soil Profile" section are analyzed using the PSHAKE program. The responses in PGA, Sa_s, and AF are recorded and compared to each other. The result from Case 2 verified in the "Framework of Stochastic Site Response Analysis" section is used as a reference solution for the rest of the cases.

Peak Ground Acceleration

Fig. 7 illustrates the comparison between the statistical distributions of PGA at the surface obtained from different models. These distributions are compared with the PGA at the bedrock, which is represented by vertical lines. The uncertainty of soil property is presented by the mean and standard deviation values that are shown in each subfigure. It can be seen that the histogram of density (Case 3) shows the lowest dispersion in the PGA at the surface with a minimum value of 0.057 for standard deviation. Comparing with the second case, the differences in mean PGA at the surface are

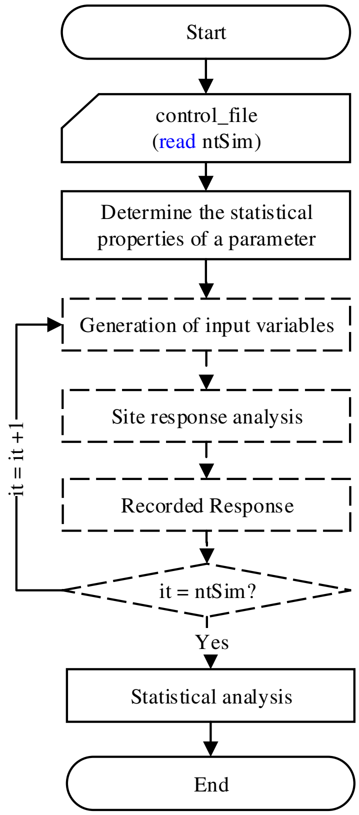

Fig. 4. Schematic diagram of stochastic analysis.

13.81%, 4.28%, and 0.58% for the first, third, and fourth cases, respectively. These results indicate that density is more efficient on the performance of the site response.

The discrepancy in PGA at the surface of the different models is also explained through cumulative distribution function (CDF). The CDF of a probability distribution, $F(x)$, is a function that defines the probability of the random variable which takes a value less than or equal to x and is expressed as

$$\mathrm{F}(\mathrm{x}) = P(X \leq x) \tag{12}$$

The sensitivity of PGA at the surface for the various models is evaluated in Fig. 8 through CDF. Referring to Case 2 with a PGA of 0.514 g is used to determine the changes in the CDF for other cases. It is observed that the CDF shifts rightward with variability in the unit weight, which implies a decrease in the probability, which is opposite of Case 1. Note that the CDF from Case 4 has a similar effect to Case 2 with a negligible difference. The alteration in the PGA at the surface for different models is summarized in Table 3. The table shows that the nonlinear property of soil is the least effective parameter to be considered for the PGA that corresponds to the 15.08% probability. In addition, the uncertainty in shear wave velocity using log-normal distribution is the most effective parameter, with the associated change of 40.12% in the probability. This happens because the density of the soil profile has a lesser effect on the stiffness of the soil profile compared to the shear wave velocity. The results obtained for PGA are found to be the same as investigated by Rathje et al. (2010).

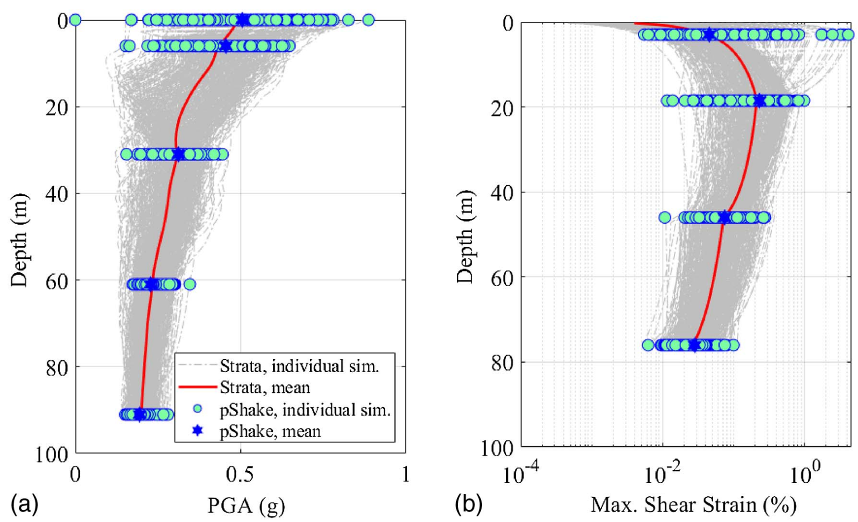

Fig. 5. PGA and maximum shear strain profiles of PSHAKE and Strata: (a) PGA (g); and (b) max. shear strain (%).

Table 2. Comparisons of mean PGA and maximum shear strain between PSHAKE and Strata

PGA (g)				Max. shear strain (%)			
Depth (m)	PSHAKE	Strata	Difference (%)	Depth (m)	PSHAKE	Strata	Difference (%)
0.0	0.514	0.486	5.86	3.0	0.040	0.039	1.86
6.0	0.455	0.438	3.80	18.5	0.232	0.212	9.70
31.0	0.312	0.306	1.84	46.0	0.075	0.072	3.44
61.0	0.227	0.235	−3.10	76.0	0.028	0.026	8.33
91.0	0.195	0.198	−1.80	—	—	—	—

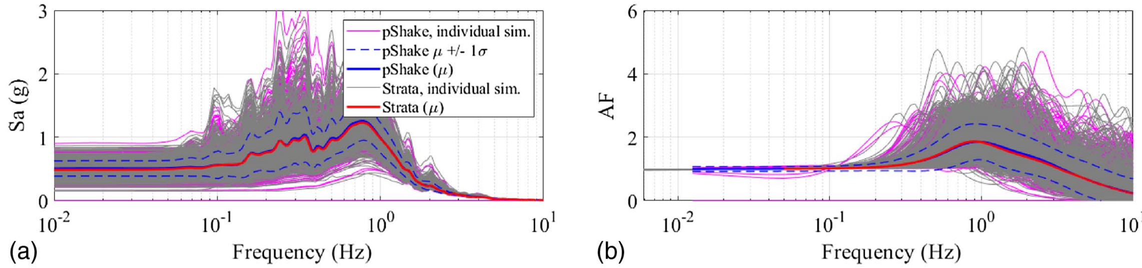

Fig. 6. Surface response spectra and amplification functions of PSHAKE and Strata: (a) surface response spectra; and (b) amplification function.

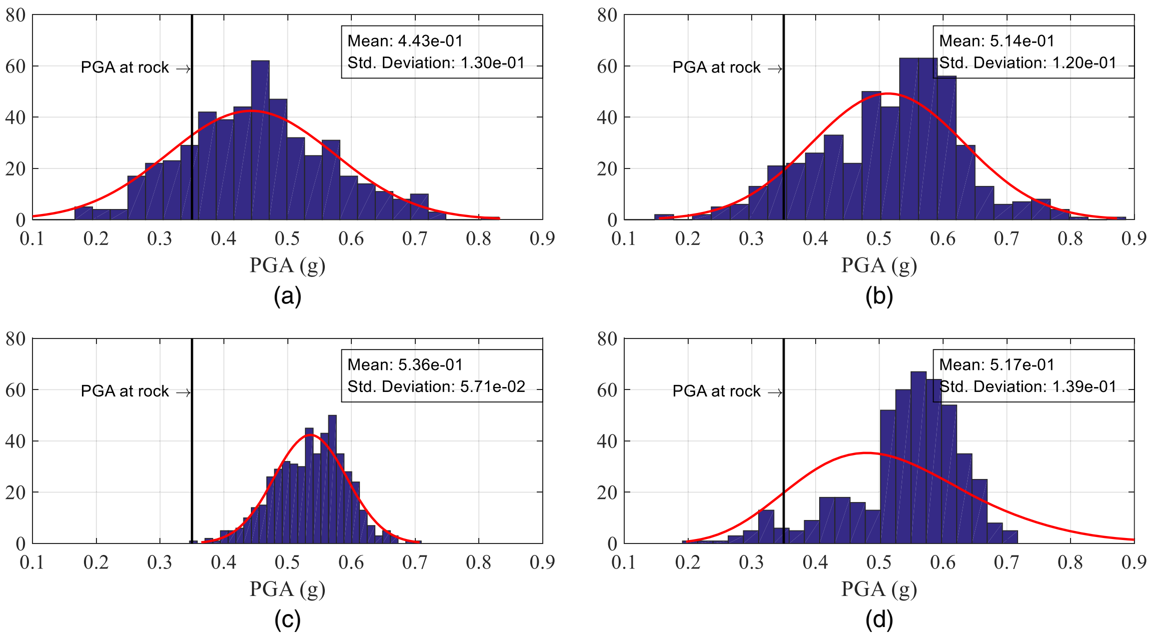

Fig. 7. Probabilistic distribution of the PGA at the surface: (a) Case 1; (b) Case 2; (c) Case 3; and (d) Case 4.

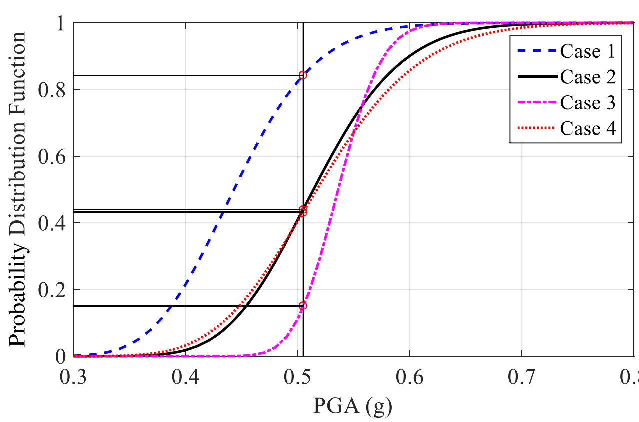

Fig. 8. Cumulative distribution function of PGA at the surface for different models.

Acceleration Response Spectra

The statistical response spectrum of spectral accelerations at the surface is shown in Fig. 9. In general, the uncertainty in density shows the smallest dispersion in the response that manifests the negligible effect on the acceleration response spectra. Fig. 10 considers the sensitivity of soil characteristics in site response analysis with the mean (μ) and standard deviation (σ) in the response obtained from Fig. 9.

Table 3. Variations in probability of PGA with different cases

Case	Case 1	Case 2	Case 3	Case 4
Value of probability	84.19	44.07	15.08	43.22
Change (%)	40.12	0.00	−28.99	−0.85

In Fig. 10(a), the difference in the mean surface response spectra calculated from the first case is lower than the second case, with the maximum reduction of 11.14%. Although the log-normal distribution is considered for V_s variability in the first two cases with different approaches (log-normal distribution and Toro model), Case 1 has a reduction at periods less than 1.0 s. Additionally, a concurrence is found for Case 3, although it has an increment of 16.97% occurring at 0.8 s. The variability of nonlinear soil causes a decrement in the mean spectral acceleration, as shown in Fig. 10(a), and a maximum decrement of 22.08% occurs at periods less than 1.0 s. This manifests the softness of the soil profile (i.e., the softer material modeling with higher damping) effect *AF* more than the stiffness of the soil profile (Rathje et al. 2010). Another observation

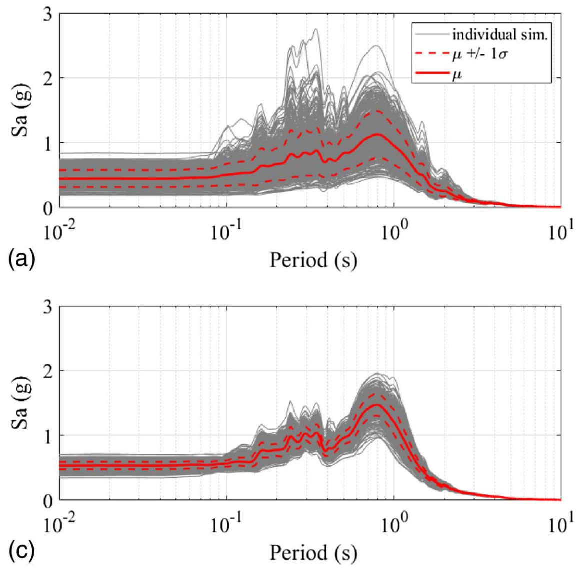

Fig. 9. Surface response spectra for different models: (a) Case 1; (b) Case 2; (c) Case 3; and (d) Case 4.

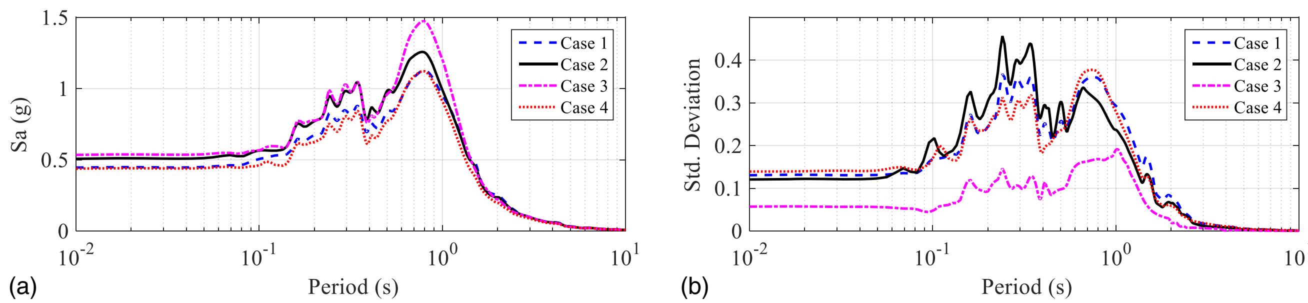

Fig. 10. (a) Mean surface response spectra; and (b) standard deviation for different models.

is the standard deviations of Sa_s which is illustrated in Fig. 10(b). The smallest σ_{Sa} in Case 3 occurs in the period range (less than 0.2 s), while other cases have an increasing trend at periods less than 0.35 s and a decreasing trend at periods greater than 0.7 s. Based on the results obtained, it is worth mentioning that the variation of unit weight yields the strongest mean surface spectra and the smallest standard deviation. According to the wave propagation theory, the site response depends on the unit weight and shear wave velocity (Aki and Richards 2002). However, in this research, both density and V_s are simulated with the same value of COV, which is assumed to be equal to 0.3; hence, the higher mean surface spectra can be found in Case 2. Besides, the frequency of ground motion may amplify or deamplify the site response if the site medium contains a high frequency.

In the ground response analysis, the amplification can be defined either by amplification factor or by a frequency-independent amplification factor, F_a (Barani et al. 2013). The F_a is defined as a ratio of the acceleration response spectrum intensity at the surface, ASI^s, to the acceleration response spectrum intensity at the rock outcrop, ASI^r (Von Thun et al. 1988)

$$F_a = \frac{ASI^s}{ASI^r} \tag{13}$$

where the acceleration response spectrum intensity can be expressed by integrating the acceleration response spectrum, $S_a(T)$, in the range of spectra period, T, (Aki 1993)

$$ASI = \int_{0.05}^{2.5} S_a(T)dT \tag{14}$$

Fig. 11 is the histogram of F_a for the different models. The comparative analysis for the mean and standard deviations of F_a is presented. The distributions of frequency-independent amplification factors depend on the shape of a response spectra. In particular, randomizing the nonlinear properties of the soil profile are more indicative for the higher standard deviations of F_a. The histogram of Case 3 shows the lowest dispersion in the distribution of the F_a with 0.181 of the standard deviation. Following the difference between Cases 1 and 2, it can be deduced that the selection of the site-specific probability distribution of geotechnical parameters has a great impact on the probabilistic soil models.

In the Toro model, shear wave velocities are simulated based on the mean and standard deviation of soil properties that are obtained from a large number of data sets collected from many sites. Thus, the variability of geotechnical parameters within this specific site does not represent the others. This variability is also responsible for the difference in the first two cases. Therefore, it is necessary to consider the probabilistic distribution of soil properties carefully to make a consistent group of parameters for the site analysis.

Amplification Function

Fig. 12 shows the comparison of the mean and standard deviation of amplification factors. The trend of AFs is the same as in Fig. 10.

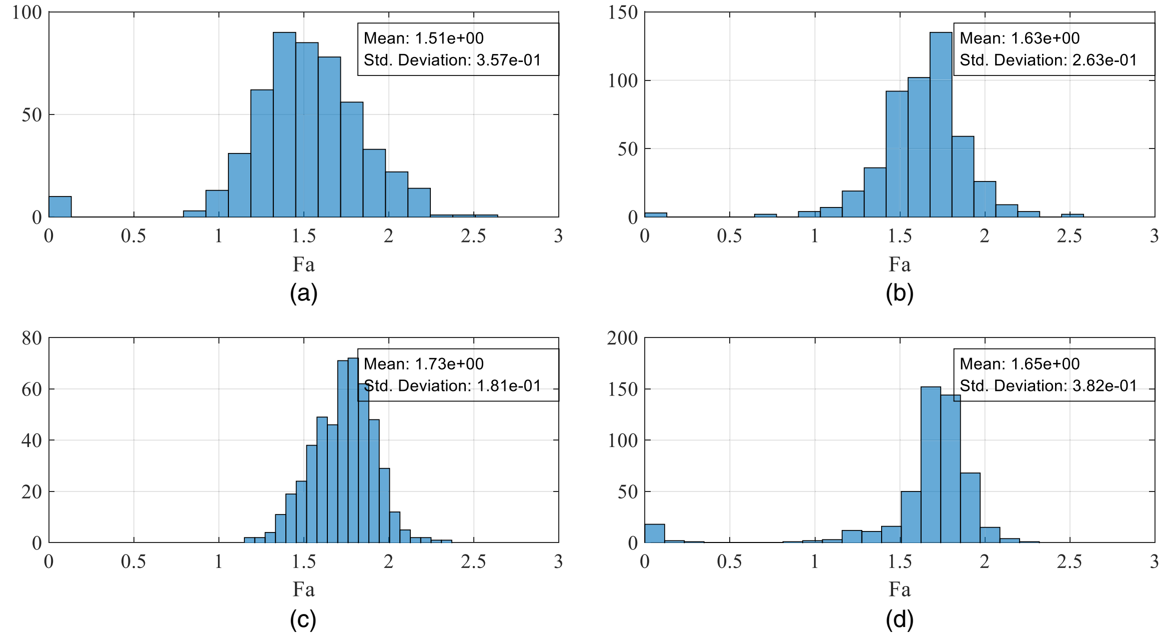

Fig. 11. Histogram distribution of F_a for different models: (a) Case 1; (b) Case 2; (c) Case 3; and (d) Case 4.

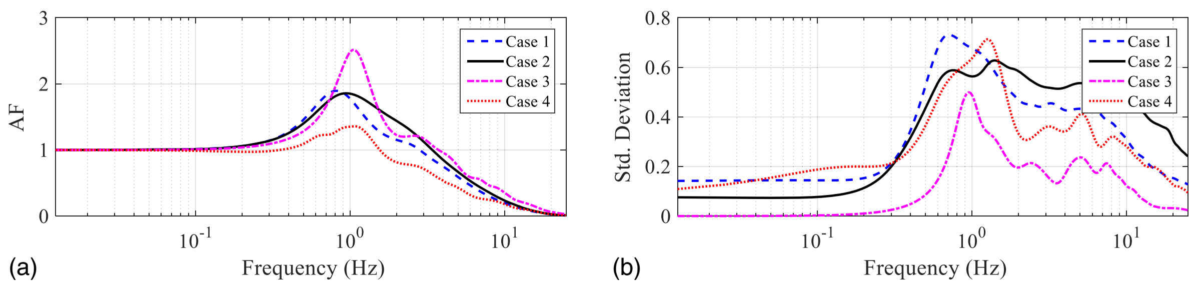

Fig. 12. Mean amplification functions and standard deviation for different models: (a) mean amplification function; and (b) standard deviation.

In Fig. 12(a), the mean AFs at lower frequencies are smoother than those for the higher frequencies. The uncertainty in the V_s with the log-normal distribution and the Toro model is the same in the range of frequencies lower than 0.8 Hz. It is also noticeable that when considering the uncertainty in the unit weight, the mean AF is similar in the shape with Case 2 except the higher peak occurs at around frequency of 1 Hz. Considering the effect of uncertainties in the nonlinear soil, the mean AF has a lower effect with a reduction of about 4%–26% compared with the second case. Comparing the standard deviation values in Fig. 12(b), the results show that the values from Case 3 indicate the lower effect. Moreover, standard deviations observed from Case 4 are close to the low frequency and have a large difference at high frequency (38%–60%).

This research investigates the influence of input parameters of the soil and shows that nonlinear soil properties with probabilistic distribution significantly affect the soil response. The outcomes obtained in this research, specifically in the AF of soil deposit, are found to be in good agreement with the investigation by Aki (1993).

Conclusions

This study presents an approach for the probabilistic procedure for site response analysis that is implemented in the computer program PSHAKE. The framework allows considering the uncertainties in geotechnical properties of soil deposit associated with the soil profile and its material parameters. The numerical simulation is presented for a specific site in the San Fernando Valley of Southern California. Verification and validation of the process are performed for the uncertainty in the V_S using the Toro approach. The compatibility of the proposed procedure is considered with the Strata program based on the agreement in response analyses (i.e., PGA profile, maximum shear strain profile, surface response spectra, and amplification factor). Thus, the solution can be used effectively for statistical analysis in predicting the site response.

Through the sensitivity analysis, the effects of the uncertain properties, including the shear wave velocity, the unit weight, and the shear modulus reduction and damping, on site responses are examined by the various probabilistic distributions. The main findings of the study are summarized below:

- It is significant to consider the varying probabilistic distributions of soil profiles for the generation of site response more sophisticatedly. The results obtained confirm that the modeling of the uncertainties in the soil properties has a significant impact on the mean and standard deviation in the statistical analysis.
- Comparatively, the variability in V_s from the Toro model is found to be similar to the log-normal distribution of the geotechnical profiles of soil in Sa_s and AF for periods greater than 1.0 s. Conversely, in the range of lower periods, the response from the

Toro approach is more effective than a log-normal approach with maximum reductions of 11.14% and 20.86% in Sa_s and AF, respectively.
- It has been found that the spatial variability in shear wave velocity using log-normal distribution is the most effective parameter with the change in probability of 40.12% in PGA at the surface.
- The randomness in the unit weight has less dispersion in the surface response. The mean Sa_s and AF are consistent with those from the V_S randomization using the Toro approach, although the higher peak occurs around 0.8 s.
- Randomness in material degradation follows the maximum decrements of 22.08% and 43.44% in Sa_s and AF at a period of less than 1.0 s. Regarding the PGA at the surface, the results show that material degradation has a smaller effect that corresponds to the change of 0.85%.

Data Availability Statement

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions.

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