IASMiRT

SMiRT 26
50 Anniversary Berlin/Potsdam

Transactions, **SMiRT-26**
Berlin/Potsdam, Germany, July 10-15, 2022
Division V

A COMPUTATIONALLY EFFICIENT SOIL PARAMETER RANDOMIZATION SCHEME FOR NONLINEAR SOIL-STRUCTURE INTERACTION ANALYSIS

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ABSTRACT

The soil input parameters typically needed for Finite Element (FE) analysis of a nonlinear Soil-Structure-Interaction (SSI) system in commercially available computer programs do not often correspond one-to-one to the parameters typically randomized to control nonlinear soil behavior in a traditional Site Response Analysis (SRA). The material shear stress-strain backbone curve is usually required as direct input in an SSI FE analysis program instead of low-strain properties and strain-dependent modulus reduction curves. The non-Masing damping curves may also be needed as input. These input parameters are not fully independent, and the randomization scheme used to support a probabilistic analysis framework should account for the underlying correlation. This article provides a computationally efficient procedure for randomization of the soil input parameters often needed for nonlinear FE analysis of SSI systems. The randomization scheme presented can be implemented using either Latin Hypercube Simulation (LHS) or the more traditional Monte Carlo Simulation (MCS). An example case study using LHS is presented to generate realizations of stress-strain backbone and damping curves, and the stability of the simulated soil response distributions is compared using two randomized samples of different sizes. The technique is demonstrated in a case study using probabilistically randomized FE simulations of a layered soil column excited by input motion at depth and comparing the distributions of surface motion responses.

INTRODUCTION

The seismic response of layered soil is often treated probabilistically in both SRA and SSI applications to account for uncertainty and variation of site geomaterial properties. When modeling the nonlinear behavior of geomaterials using approaches that utilize equivalent-linear material properties, randomization techniques developed for probabilistic SRA have been adopted to probabilistic SSI with relative ease. However, when defining geomaterial shear behavior using explicitly nonlinear hysteretic material properties as input, adjustments to the randomization methodologies developed for probabilistic SRA can significantly improve the pre-processing convenience for the probabilistic SSI analyses that rely on finite element (FE) formulations.

It is common in SRA to define the strain-dependent degradation in soil material shear stiffness using G/G_{max} curves, where G_{max} is the initial shear stiffness that corresponds to the soil low-strain shear-wave velocity (V_s). Strain-dependent damping is also considered via damping curves. Typical randomization procedures used in traditional SRA applications create realizations of V_s values, G/G_{max} curves and damping curves (Darendeli (2001)). However, the process for randomizing the G/G_{max} curves is needlessly inconvenient in those SSI analysis applications in which the software directly uses the material shear stress-strain backbone curve at discrete data points rather than V_s values and G/G_{max} curves. The defining parameters for nonlinear backbone curves are: (1) the initial soil shear stiffness G_{max}, (2) the soil shear strength τ_{max}, and (3) the change in shape with shear strain γ until the stress is asymptotic to τ_{max}. Figure 1 illustrates the relationship between these parameters. Once the stress-strain curve is defined, it is input to the FE program as discrete stress-strain data points for the expected strain range of the soil response.

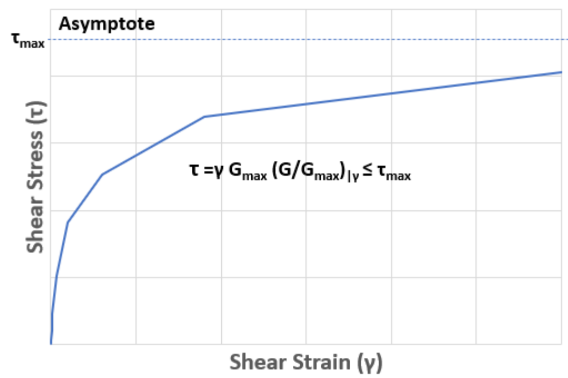


Figure 1. Representation of Soil Nonlinear Behavior through Shear Stress-Strain Backbone Curve

METHODOLOGY DESCRIPTION

The proposed methodology consists of the following four steps that are implemented directly on the shear stress-strain backbone curve coordinates:

1. Generate a random shear strain factor based on G/G_{max}; apply it to the strain ordinates.
2. Generate a random stress factor based on low strain G_{max} and τ_{max}; apply it to the stress ordinates.

The following sections describe each step.

Randomization of the Strain Ordinates

The empirical G/G_{max} soil curves are typically obtained by fitting a predefined shape to the measured test data which are usually obtained at small strains. For a given soil material, the G/G_{max} curve is a function of shear strain – typically represented by a power-law relationship. For example, the hyperbolic model, patterned after Darendeli (2001), is defined by:

$$\frac{G}{G_{max}} = \frac{1}{1+\left(\frac{\gamma}{\gamma_r}\right)^a} \tag{1}$$

where γ_r is the reference strain corresponding to $G/G_{max} = 0.5$ and a is a curvature coefficient. Both γ_r and a are obtained by fitting the G/G_{max} curves to laboratory test data for a given soil. Darendeli (2001) also suggested upper bound and lower bound values for G/G_{max} curves.

Evaluation of the range of the G/G_{max} values observed in experimental test data, as well as the generic range suggested in the literature, such as Darendeli (2001), indicates a relatively constant logarithmic standard deviation in the strain ordinates at a given G/G_{max} value over the majority of the strain range in the logarithmic space (except at very low and high strains). This value can be estimated based on the range of γ_r indicated by geotechnical test data for a given soil or, in the absence of soil-specific test data, the generic estimates of Darendeli (2001). The strain ordinate randomizing factors are applied to the soil stress-strain base curve to scale all strain ordinates equally. The resulting stress-strain curves include the desired variability band in G/G_{max}. This technique alleviates the need to constrain the G/G_{max} to be between 0 and

1 if they are randomized directly. In addition, it includes the corresponding variability in G_{max}, which is discussed in the next section. Note that the randomization of the strain ordinates does not need to determine γ_r or other parameters in Equation (1).

Randomization of Stress Ordinate at Low Strain

The low-strain shear modulus G_{max} is the initial slope of the stress-strain curve. This initial slope is the product of V_s^2 and material mass density. Considering that the variability of the mass density is negligible compared to the variability in soil shear-wave velocity, the logarithmic standard deviation of G_{max} is about twice that of V_s.

Since the randomization of the strain ordinate shifts all the data points in the stress-strain backbone curve right or left, it results in partial randomization of the initial shear strain G_{max}. Therefore, the stress ordinate randomizing factor should include only the additional variability required to achieve the target variability in G_{max}. The stress and strain ordinate randomization factors are independent. Therefore, the target logarithmic standard deviation of G_{max} should equal the square root of the sum of the squares (SRSS) of the logarithmic standard deviations in the strain and low-strain stress factors. The low-strain stress factor standard deviation is calculated using this SRSS relationship from the logarithmic standard deviations of G_{max} and that of the strain randomization factor (previous section). It is then used to generate a randomized sample of low-strain stress adjustment factors and used to modify the stress ordinates as described in the next section. The variability in G_{max} is independent of G/G_{max}, which is represented by γ_r. However, it is noted that the implementation of the proposed sampling scheme introduces a partial negative correlation between their sampled values. This artificial correlation is weak and not a significant consideration so long as the low-strain stress ordinate factor standard deviation represents the majority of the standard deviation in G_{max}, which is typical.

Randomization of Stress Ordinate at Soil Shear Strength

Laboratory soil tests are usually performed at small strains and do not account for the soil at large strains. Therefore, the treatment of soil behavior with predefined fitted curves such as the Darendeli (2001) hyperbolic model for applications in which large soil strain is expected may be invalid and the mean and randomized G/G_{max} curves of a soil layer can produce unreasonably high or low strengths at large strain values. To avoid this problem, the stress-strain curve should be constrained by the material shear strength. The shear strength can be obtained from direct shear tests or triaxial compression tests on retrieved samples. In the absence of direct shear strength test data, the Mohr-Coulomb shear strength model can be used to estimate the geomaterial shear strength. This model uses the internal friction angle and cohesion intercept to estimate the shear strength.

The logarithmic standard deviation of the geomaterial shear strengths should be obtained from the site-specific test results if available. In the absence of such test data, generic published data may be used. For example, Hoek and Brown (2018) provide standard deviations for sites with different rock mass ratios (RMR) and geologic strength indices.

Transitioning the Stress Ordinate Factors from Low-Strain to Shear Strength

For a randomized realization of the shear stress-strain curve, the stress ordinates at low strain and at τ_{max} should be sampled assuming perfect correlation since a stiffer soil is typically associated with a higher shear strength in nature. Once they are sampled, they should be combined to obtain the stress ordinate factor at any strain following the relationship below:

$$\textit{Stress randomization factor at point } i = A.\,n(i) + B.\,(1 - n(i)) \qquad (2)$$

where *A* is the low-strain stress ordinate factor, *B* is the τ_{max} stress randomization factor, and *n* is the extent of softening at point *i* compared to the initial stiffness (i.e., $G/G_{max}|_i$).

Randomization of Soil Damping

In addition to the soil stress-strain behavior, damping should also be appropriately accounted for in a probabilistic SRA or SSI analysis. Traditionally, nonlinear SRA software tools have implemented the hysteretic soil damping using the Masing Unloading/Reloading rules defined in Kramer (1996). However, the Masing rule is believed to overestimate hysteretic damping compared to the reference damping curves in most cases, especially at large shear strains. Therefore, it is recommended to use non-Masing hysteretic damping algorithms in explicit nonlinear analysis. The capability to fit any damping curves is offered by non-Masing algorithms, and realizations of the input damping curves can be used to account for uncertainty in hysteretic damping.

Test data suggests that the standard deviation of damping increases with soil strain, ε. Darendeli (2001) suggests the following relationship to estimate the standard deviation for material damping ratio, σ_D:

$$\sigma_D(\varepsilon) = e^{\phi_{15}} + e^{\phi_{16}}.D(\varepsilon) \tag{3}$$

where *D* is the mean estimate of material damping curve, and ϕ_{15} and ϕ_{16} are parameters that relate standard deviation to the mean estimate of material damping ratio.

Correlation Between Sampled Random Variables

Correlation between the randomizing factors in each geomechanical unit, based on the expected physical behavior of the soil materials, is proposed as follows:

- Stress factors at low-strain and τ_{max} have a strong positive correlation and should be modeled as perfectly correlated.
- γ_r and non-Masing damping have a strong negative correlation. A softer material dissipates more hysteretic energy. Therefore, they should be modeled as perfectly inversely correlated.
- The other variable pairs within the same geomechanical unit should be modeled as uncorrelated.

Across the different geomechanical units within a soil profile, a two-step (i.e., stress and strain ordinate) sampling of G_{max} is proposed as follows:

- The stress ordinate randomizing factors should be perfectly correlated across all units considering that most of the soil materials in a stiffer and stronger soil profile are also stiffer and stronger than the corresponding materials in a weaker soil profile.
- The strain ordinate randomizing factors should be uncorrelated across all units since there is no physical evidence of G/G_{max} dependence across different materials in a soil profile.

This implementation scheme results in a partial correlation between the sampled G_{max} for adjacent layers. Since the randomizing factors for G_{max} are the product of randomizing factors for the stress and strain ordinates, this partial correlation is strong given the typically higher variability in the former (which are modeled as perfectly correlated) than the latter (which are modeled as uncorrelated).

Pairing of Randomization Multipliers

The pairing of the randomization multipliers of independent random variables has historically been performed by the random ordering of the randomizing multipliers for each variable. Each SSI model realization from 1 to N picks a random bin number from 1 to N for each random variable where N is both the number of SSI model realizations and the number of realizations of individual random variables since these two quantities must be equal. Alternatively, the pairing has also been performed using space-filling algorithms that maximize the coverage of the multi-dimensional probability space in the aforementioned matrix while maintaining statistical independence. Either approach or a mix thereof can be used. For the case study presented in this paper, a space-filling design for the pairing of random variable sets is used since it can typically achieve a statistically stable design using a smaller sample size. The pairing of the randomization factors of dependent variables which are modeled as fully correlated should be done such that the sampling bin numbers for each realization are either the same or opposite to each other for positive and negative correlation, respectively.

Truncation of Sampling Distributions

The tails of probability distributions are often approximate fits to data and should be truncated where this approximation can lead to sampled output not supported by the data, logic, or both. A sampling truncation between ±1.65 times the standard deviation corresponds to the central 90% of the probability mass and often achieves adequate representation of the variability range while avoiding unrealistic extremes for typical sites. This truncation threshold is used in the case study presented herein.

CASE STUDY

This case study evaluates the implementation of the randomization scheme explained above on a realistic soil profile. Two randomized samples with 30 and 60 sample sizes are used to evaluate the statistical stability of the results using the LHS technique.

Model Description

The SSI model in this case study is developed using LS-DYNA (2017) by combining a nonlinear single-degree-of-freedom (SDOF) of a structure and a plane-strain FE model of a unidimensional (1D) soil column. The structure model consists of a nonlinear SDOF spring-mass-dashpot system with an initial spring stiffness of 350 kip/ft, a mass of 0.320 kip-s^2/ft, and a dashpot damping of 0.207 kip-s/ft. The SDOF spring is connected to the soil column at 11.4' below the soil ground surface. The input motion is applied at the base of the soil model in a single direction, simulating the horizontal ground motion. Figure 2 shows a schematic elevation view of the model. The soil domain in this case study is modeled with 11 unique geomechanical units. The site layering discretization for the SSI FE model and the corresponding geomaterial parameters are presented in Table 1. Some units are further split into sub-layers and/or elements. The nonlinear response of the soil is simulated using the hysteretic plasticity model in LS-DYNA. Transmitting boundary conditions are applied at the base and sides of the soil model to prevent the reflection of the outgoing seismic waves and to model an effectively "infinite" domain. This material model is a multi-yield-surface plasticity model that takes as its primary input the material shear stress versus shear strain coordinates to build the plasticity yield surface. The hysteretic response of the material under shear loading, i.e., unload-reload, is defined using reference damping curves and the non-Masing rule. The G/G_{max} and non-Masing damping curves assigned to each geomechanical unit are plotted in Figure 3.

Table 2 summarizes the logarithmic standard deviation of the randomizing factors for the shear stress-strain curves. The logarithmic standard deviations of the shear-wave velocities and shear strength are obtained from geotechnical data. The logarithmic standard deviations of the strain ordinate γ_r is obtained by examining the distribution band of G/G_{max} curves obtained from test data. The G_{max} standard deviations, $\sigma_{G_{max}}$, are twice the shear-wave velocity standard deviations, σ_{V_s}. The standard deviations of the low-strain stress randomizing factor, σ_{τ_0}, are obtained such that their SRSS combinations with the strain ordinate standard deviations, σ_{γ_r}, produce $\sigma_{G_{max}}$. The resulting randomized stress-strain and damping curves for one of the geomechanical units in this case study are shown in Figure 4 for the 30-sample set.

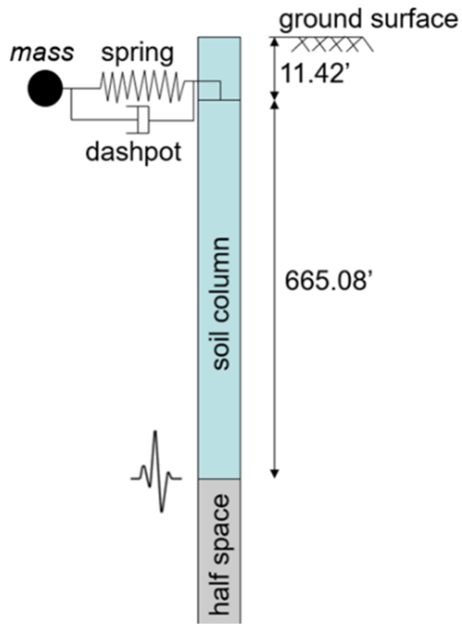


Figure 2. Schematic of 1D SSI Model

Table 1: Properties of the Base Case Soil Profile Used in the Case Study

Unit	Thickness (ft)	Unit Weight (pcf)	V_s (ft/sec)	G_{max} (ksf)	At-rest pressure (K_o)	τ_{max}(ksf)*
A	8.75	87.6	1,000	2,720	0.46	2.26 to 2.41
B	40	101.4	1,640	8,470	0.52	1.82 to 3.69
C	7.5	91.4	1,340	5,097	0.64	3.29
D	50	88.5	1,050	3,030	0.62	4.63 to 5.94
E	7.5	97.6	1,550	7,282	0.43	6.61
F	77	119.1	2,450	22,202	0.42	12.09 to 16.32
G	53	82.6	1,860	8,875	0.31	12.78
H	71	80	2,420	14,550	0.33	-+
I	62	94.9	2,690	21,326	0.42	-+
J	272	83.1	2,910	21,854	0.36	-+
K	32.5	94.9	2,580	19,618	0.55	-+
Halfspace	-	146.8	5,500	137,910	----	-+

* Shear strength varies with depth. Each geomechanical unit is discretized in the SSI model using one or more elements through the thickness.

+ No strength adjustment is made to the stress-strain curves for these geomechanical units.

The site profile in this case study is close to the border between U.S. Geological Survey (USGS) Site Classes B and C. Table 3 shows the correlation coefficients calculated using MCS for this soil profile using the proposed randomization scheme and values predicted using the Toro (1995) correlation model for USGS Class B site. The Toro model was developed using shear wave velocity data from many sites and provides ergodic estimates that should be constrained by site-specific knowledge where available. The resulting correlation structure shows agreement with the Toro model except at three layer interfaces. Two of these interfaces, i.e., the B/C and E/F layer interfaces, represent transition layers, whose Vs values are physically constrained to be between the two adjoining layers. The unconstrained Toro model would produce simulations with unrealistic Vs values in the transition layers. The third layer interface is between Units J and K, which comprise physically distinct materials and are not expected to correlate strongly. The Toro model predicts perfect correlation due to the depth of these two layers regardless of their site-specific distinction. This comparison confirmed that the randomized soil profile suite distributions are reasonable.

Table 2: Geomechanical Unit Logarithmic Standard Deviations

Unit	σ_{V_s}	$\sigma_{G_{max}}$	σ_{γ_r}	σ_{τ_0}	$\sigma_{\tau_{max}}$
A	0.21	0.42	0.25	0.34	0.20
B	0.22	0.44	0.20	0.39	0.22
C	0.15	0.31	0.125	0.28	0.22
D	0.11	0.22	0.15	0.16	0.12
E	0.21	0.42	0.125	0.40	0.30
F	0.28	0.56	0.20	0.52	0.30
G	0.21	0.42	0.15	0.39	-
H	0.21	0.42	0.15	0.39	-
I	0.26	0.52	0.15	0.50	-
J	0.16	0.32	0.25	0.20	-
K	0.36	0.72	0.25	0.68	-

Table 3: Shear Wave Velocity Inter-Layer Correlation Coefficients

Layer Interface	Recommended Sampling Scheme	Toro (1995) Model
A/B	0.7	0.5
B/C	1.0	0.6
C/ D	0.7	0.6
D/E	0.8	0.7
E/F	1.0	0.7
F/G	0.8	0.7
G/H	0.9	0.8
H/I	0.9	0.8
I/J	0.8	0.9
J/K	0.7	1.0

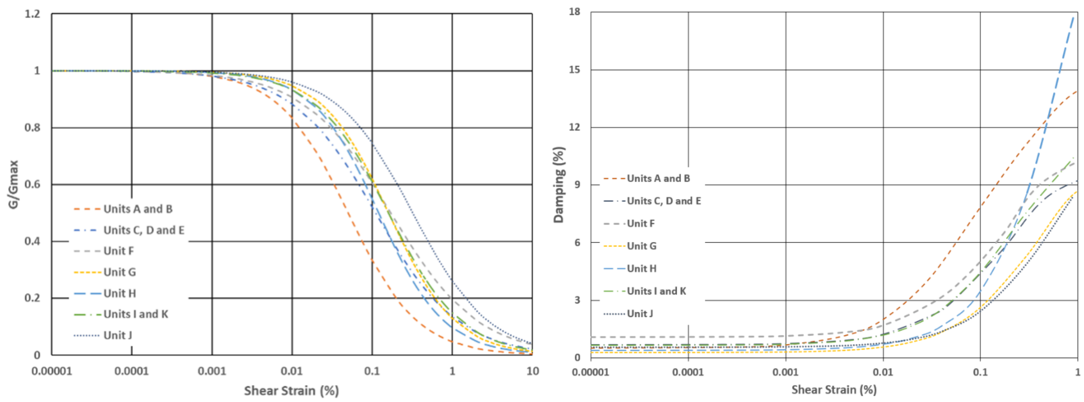


Figure 3. Soil Material Best-Estimate G/G_{max} (left) and Damping Curves (right)

Site Response Evaluation

Two horizontal input ground motion time history records are used in this case study to represent two hazard levels: the smaller ground motion amplitudes represent a hypothetical 2,500-year return period (RP) hazard level and the larger ground motion amplitudes represent a hypothetical 10,000-year RP hazard level. These two hazard levels are selected to evaluate the effects of the randomization scheme presented in this study on the soil responses in both the linear and nonlinear response ranges. The 10,000-year return period motion is postulated to be 2.4 times the ground motion record corresponding to the 2,500-year return period. These input ground motions are applied to the base of the soil columns in the randomized SSI models.

The amplified response spectra (ARS) at the base of the SDOF spring are shown in Figure 5 and Figure 6 for 2,500-year RP and 10,000 RP hazard levels, respectively. The same figures also show the corresponding outcropped input response spectra. As can be seen, the ARS for the 30-sample and 60-sample sets are nearly identical for both ground motion levels. This indicates that the LHS sampling with 30 idealizations of the soil profile achieves reasonable response statistical stability. The ARS at other soil elevations show a similar conclusion. Since this result may be specific to this case study, a sensitivity study is recommended to determine the adequate number of idealizations on a case-by-case basis until sufficient case studies are available to support general recommendations.

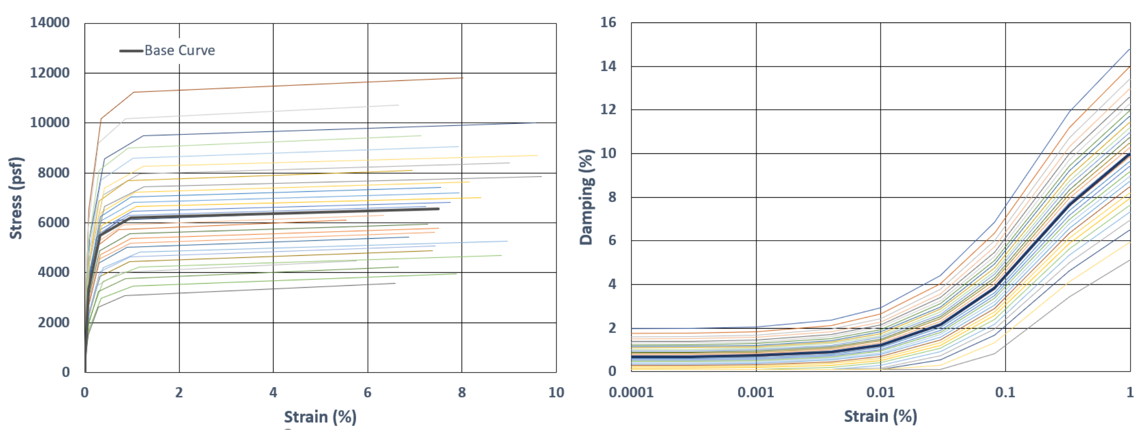
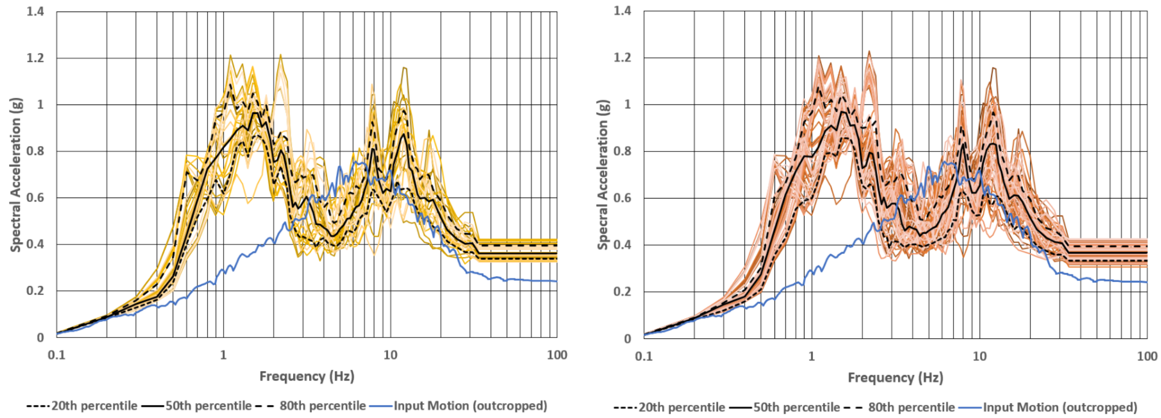
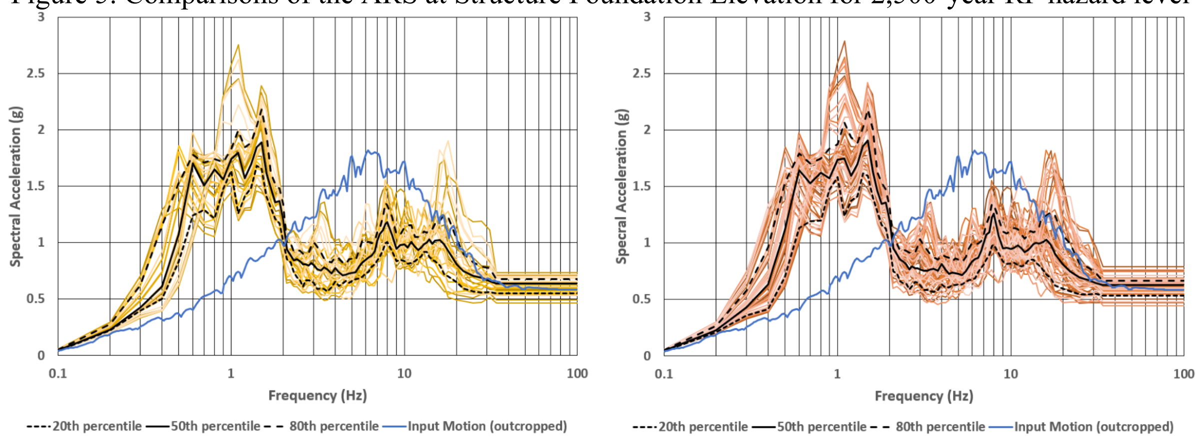


Figure 4. Randomized Stress-Strain (left) and Damping (right) Curves for Unit F



2,500-year RP Input, 30 simulations   2,500-year RP Input, 60 simulations

Figure 5. Comparisons of the ARS at Structure Foundation Elevation for 2,500-year RP hazard level



10,000-year RP Input, 30 simulations   10,000-year RP Input, 60 simulations

Figure 6. Comparisons of the ARS at Structure Foundation Elevation for 10,000-year RP hazard level

SUMMARY AND CONCLUSION

This article presents an efficient procedure for direct randomization of the soil stress-strain and damping curves, which are typically the input required for soil materials of nonlinear SSI systems in commercially available FE analysis software. This randomization scheme can be implemented to support probabilistic seismic response analyses using either the LHS or the MCS sampling methods. This randomization scheme is implemented in four main steps using three factors that control the randomized backbone curves: the shear strain ordinate factor, the low-strain shear stress ordinate factor, and the stress factor at shear strength. Determination of logarithmic standard deviations for each factor from available soil data is discussed. The recommended sampling correlations between these parameters for each soil material within the soil profile, and between different soil materials within the profile are described.

A case study is presented using a 1D soil column to demonstrate the process. The soil domain in this case study is modeled with 11 unique geomechanical units. The stress-strain and damping curves are randomized following the proposed technique using two LHS samples of different sizes. The resulting soil profile suites and the statistical stability of SSI simulation results are investigated. The randomized soil profiles show reasonable agreement in the correlation structure between the different geomechanical units within the profile with the Toro model. The distributions of simulated amplified response spectra are shown to be statistically stable in both the linear and nonlinear response domains when comparing results using 30 LHS samples to those using 60 samples. This conclusion may be case-specific and it is recommended to perform a sensitivity study for individual applications until general recommendations are developed.

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