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(Article begins on next page)

GENERATING GROUND MOTIONS USING THE FOURIER AMPLITUDE SPECTRUM

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In this paper a simplified method aimed at generating ground motions records using a Fourier amplitude spectrum model obtained by a response spectrum is presented. The use of white noise with specific conditions on the variance and inter-frequency correlation allows to get a realistic variability of the Fourier amplitude spectrum. Moreover, a two-corner frequency model is defined from empirical ground-motion data and a filter is applied to capture the attenuation at high frequencies. The generated series of stochastic ground motions accurately match the mean value of the target response spectrum. The procedure was tested on an Italian site and results showed excellent matching in terms of mean and dispersion values with either the median obtained from ground motion prediction equations and conditional mean spectra. The advantage of the proposed methodology is that time-histories can be generated with low computational effort, they do not need scaling or frequency content adjustments and are spectrum compatible with a given target spectrum.

KEYWORDS

Stochastic ground motion generation, phase derivatives, Fourier amplitude spectrum, target response spectrum, logistic distribution

INTRODUCTION

Real ground motion records are commonly used as input in structural dynamic analyses. The access to seismic record databases worldwide has been increasingly facilitated over the past few decades. The quality and size of those databases have also been constantly increasing. However, despite the efforts to extend the network of earthquake sensors, there are still some areas of the world where the earthquake records might not be enough to implement stochastic analyses. For instance, the Chilean fault system generates extremely strong and long ground motions that are not sufficiently represented in current databases. Moreover, there is still a lack of near-source records from large events making it difficult to establish whether observations are well representative of possible motions. In such cases it might be necessary to follow alternative methods that allow to generate synthetic ground motion records. Douglas and Aochi (2008)¹ presented a review of several methodologies that can be used to predict earthquake ground motions both in terms of time-histories and ground-motion intensity measures. In this research the focus is on methods that can be used to transform event parameters to acceleration time-histories. Generally, it is possible to categorize all methodologies in two approaches: physics-based and experimental-based. The first approach consists of mathematical models based on physical principles, while the second one relies on empirical data collected from previous seismic events fitted using various techniques. The models resulting from the second approach are not necessarily based on physical principles. Examples of physic-based approaches are Finite Element Methods (FEMs) and Spectral Element Methods (SEMs). FEMs and SEMs can be effectively used to model full 3D earthquake wave propagation even for strong motions², also considering variations of seismic wave velocity, density, and crustal thickness³. Nevertheless, they require high-resolution input data with considerable computational effort. On the other hand, experimental-based methods can be used to generate ground motion by filtering a random signal's frequency content and multiplying it by an envelope function. The frequency content and envelope function are usually defined through prediction equations such as those introduced by Sabetta and Pugliese (1996)⁴ and Rathje et al. (1998)⁵. Some of these methodologies have been implemented in free and user-friendly software such as SIMQKE⁶ and OPENSIGNAL⁷ that embed several features to select ground motion records and do basic signal processing operations.

The lack of physical principles of the experimental-based methods has shifted the focus of researchers on the first category, which offers the possibility to find solutions to a larger number of case studies. Boore (2003)⁸ proposed one of the most exhaustive and simple stochastic methods based on the physics of the earthquake process and wave propagation. A Fourier Amplitude Spectrum (FAS) model is estimated using a point-source spectrum model, which

57 is transferred to the analyzed site by means of anelastic and geometric attenuation. The obtained FAS is used to filter
58 a Gaussian white noise by following the same procedure used by the experimental approach. The natural evolution of
59 this method is the discretization of the complex geometry of a given fault by combining several points-source spectra.
60 Atkinson and Assatourians (2014)⁹ described the implementation and validation of such methodology. In addition, a
61 relationship between the response spectrum and the Fourier Amplitude Spectrum (FAS) was proposed by Gasparini
62 and Vanmarcke (1976)¹⁰. In their research, random vibration theory is used to define the power spectral density
63 function from a response spectrum through an iterative process. The FAS is obtained by energy equilibrium using the
64 power spectral density function. Then, time histories are computed by superposition of sine waves shaped through an
65 envelope function to accomplish non-stationarity. FAS models from this method are often inconsistent in low and
66 high frequency ranges and require scaling to match the response spectrum. Thus, a process of adjustment in the
67 frequency domain is necessary to improve the spectral matching.
68

69 In this paper, a new method to define a FAS model based on physics assumptions is proposed and used to generate
70 spectrum compatible stochastic ground motions with respect to a given target spectrum. The approach is an extension
71 of the stochastic simulation method proposed by Boore (2003)⁸. Compared to the original method, the first novelty of
72 the proposed approach consists in adjusting the FAS model so that the simulated mean spectrum closely matches a
73 target response spectrum. The second novelty concerns the introduction of phase derivatives. Typically, a white noise
74 is windowed by an envelope function in the time domain and then filtered in the frequency domain. The effect of such
75 windowing is a variation of the phase derivatives distribution (i.e., the derivative of phase angles) in the frequency
76 domain. Their importance in signal non-stationarity was pointed out for the first time by Ohsaki (1979)¹¹. The
77 proposed phase derivatives distribution, consistent with magnitude, rupture distance and shear-wave velocity, allows
78 to achieve time non-stationarity. Stochastic ground motions generated through this procedure show mean value and
79 dispersion consistent with a target spectrum and an inter-frequency correlation consistent with the seismic records.
80

81 The proposed approach is intended to be used to generate time histories for use in nonlinear structural analyses when
82 actual seismic records are missing or not enough to represent possible ground motions. It is also intended to be used
83 along with the current seismic codes. Therefore, the method includes considerations relying on the elastic response
84 spectrum. As several researchers pointed out the elastic response spectrum in association with the peak ground
85 acceleration (PGA) might not be the most effective analysis tool to quantify inelastic deformations.^{12,13} Nonlinear
86 methods and probabilistic approaches to determine design seismic demands might be a better analysis tool and in some
87 cases have shown better performances^{14,15}, especially in the case of pulse-like ground motions¹⁶ and rupture directivity
88 effects¹⁷ which are potentially more damaging. The outcome of this research is however envisioned as a practical tool
89 that can be effectively used by professional engineers, who comply with current design codes.
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91 **PROPOSED METHODOLOGY BASED ON A FOURIER AMPLITUDE SPECTRUM MODEL**

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93 The work-flow is based on the methodology presented by Boore (2003)⁸, where the frequency content of a white noise
94 is filtered by means of a FAS model and inverted in the time domain. The first step of the proposed methodology is
95 based on the generation of a FAS model from a target response spectrum. The additive double corner frequency model
96 proposed by Boore et al. (2014)¹⁸ was adopted. Considering a flat high-frequency acceleration spectrum and equating
97 the double corner frequencies ($f_a; f_b$) model to a single corner frequency (f_c) model, f_b can be related to f_a and f_c through
98 Equation (1):
99

$$100 \quad f_b = f_a \sqrt{\frac{(f_c / f_a)^2 - (1 - \varepsilon)}{\varepsilon}} \quad (1)$$

101
102 where ε is a weighting parameter. Therefore, it is possible to write the double corner FAS model proposed by as shown
103 in Equation (2):
104

105
$$A(f) = C \left[\frac{f^2(1-\varepsilon)}{1 + \left(\frac{f}{f_a}\right)^2} + \frac{f^2\varepsilon}{1 + \frac{f^2}{(f_c^2 - f_a^2)/\varepsilon + f_a^2}} \right] \quad (2)$$

106 where C is a scaling parameter. This is the generalized FAS model used to create the frequency amplitudes.
 107 To better represent the Fourier amplitudes at high frequencies, the model can be modified by applying a filter. In this
 108 study, the attenuation at high frequencies is modeled by applying the k filter¹⁹ as described in Equation (3).
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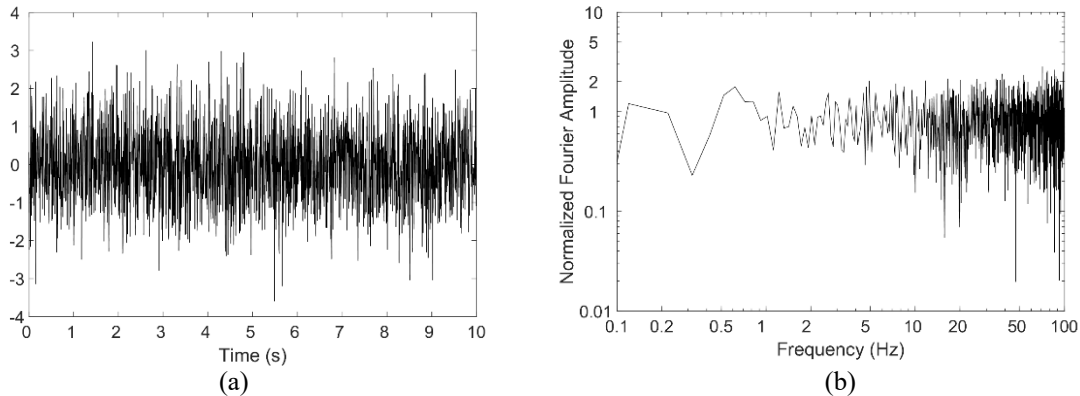
111
$$D(f) = e^{-\pi k f} \quad (3)$$

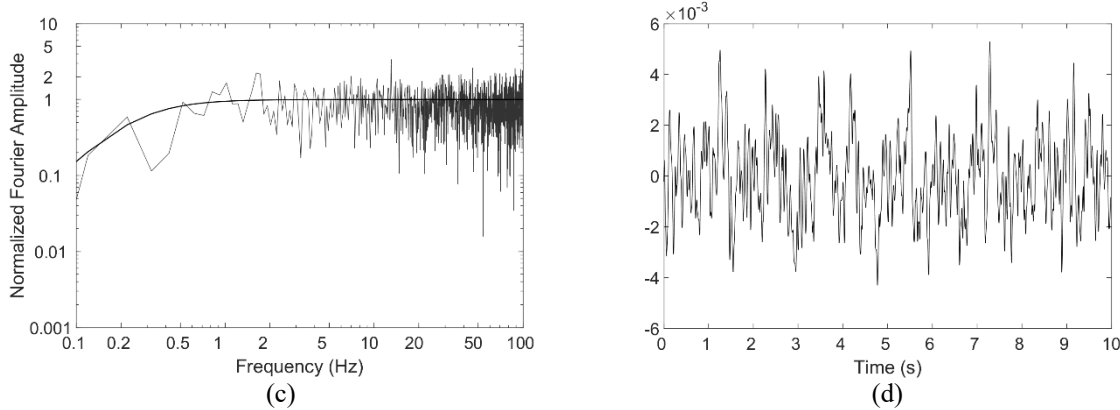
112 The parameters ε , f_a and C should be thoroughly calibrated to match the low frequency part of the target response
 113 spectrum, while a proper value of k should be selected to fit the high frequency part. A novel procedure to determine
 114 the abovementioned variables was developed. It consists of the following steps:
 115

- 116 1. A target spectrum associated to a specific value of moment magnitude (M) is computed either from ground motion
 117 prediction equations or using the conditional mean spectrum.
- 118 2. Twenty white noise samples are generated. No time windowing is applied. The duration of the signal should be
 119 properly set as it affects the spectrum.²⁰⁻²² To demonstrate the procedure a 10 s white noise is analyzed as this
 120 duration can be considered a lower limit to provide enough frequency resolution (Figure 1a). For each signal, the
 121 Fast Fourier Transform is computed, and the amplitude normalized by its root mean square (Figure 1b). The FAS
 122 of each sample is multiplied by the ω -square model according to Aki (1967)²³ as described in Equation (4).

123
 124
$$\alpha(f) = \frac{2\pi f^2}{1 + \left(\frac{f}{f_c}\right)^2} \quad (4)$$

125 The corner frequency value (f_c) is set based on the moment magnitude M associated to the target spectrum, and it
 126 is computed as $\log(f_c) = 2.623 - 0.5M$.²⁴ Amplitudes are then normalized by root mean square (Figure 1c).
 127 Finally, the time history can be obtained through the inverse Fourier Transform (Figure 1d).
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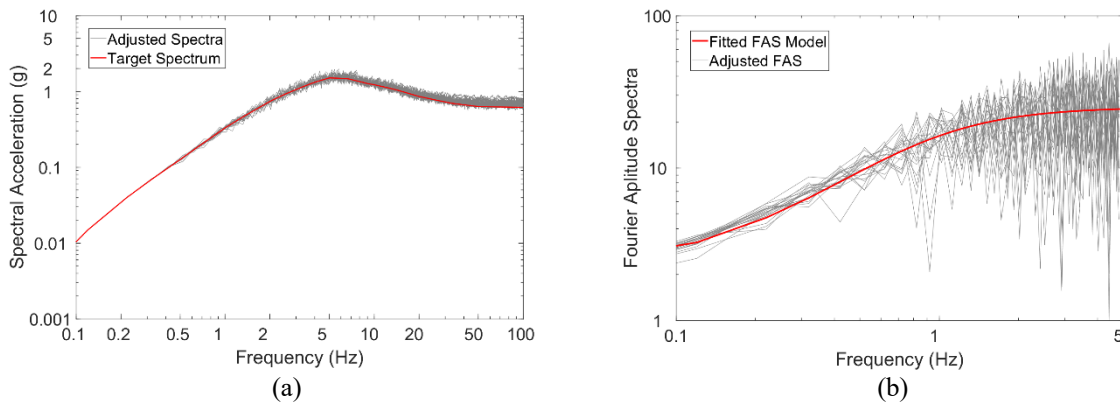


130
131 **Figure 1 - Description of the white noise generation and scaling process: (a) white noise generation; (b)**
132 **Fourier amplitude spectrum computation and normalization by its root mean square; (c) Fourier amplitude**
133 **spectrum scaled by the ω -square model; (d) time history obtained through inverse Fourier transform.**
134

- 135 3. To ensure that the FAS matches the target spectrum, iterative adjustments are performed until reaching an
136 acceptable mismatch. The iterative adjustments consist in multiplying the current Fourier amplitude (FA_i) by the
137 ratio between the spectral acceleration of the target spectrum (Sa_T) and the spectral acceleration of the current
138 FAS (Sa_i) (Figure 2a). The following formula (Equation (5)) describes the adjustment procedure.

139
140
$$FA_{i+1} = FA_i \frac{Sa_T}{Sa_i} \quad (5)$$

- 141
142 4. Non-linear regressions are used to estimate ε , f_a , and C (Figure 2b) needed for the FAS model (Equation (1)). The
143 *least mean square* algorithm was used to perform nonlinear curve fitting. The algorithm estimates the best values
144 for ε , f_a , and C that fits the nonlinear FAS model to the data obtained in the previous step.



146
147 **Figure 2 - (a) Adjusted response spectra and (b) Fourier amplitude spectra of the adjusted samples.**
148

- 149 5. Observations are generated by the calibrated FAS model defined in previous steps. The k filter in Equation (3) is
150 then applied to the observation. A tentative value of k should be selected here. Following the recommendations
151 of Boore and Joyner (1997)²⁵, a k value of 0.04 should be adequate as a first guess for a generic rock site. The
152 procedure to generate different observations can be summarized as follow:

- 153 a. Random Fourier amplitudes ($\ln A(f)$) are computed using Equation (6) according to a multivariate
154 normal distribution²⁶ characterized by a mean vector $FA(\varepsilon, f_a, C, f_c, f)$, where FA is the fitted FAS
155 model, and a covariance matrix $\Sigma(f)$:

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$$\ln A(f) \sim N[FA(C, f_a, \varepsilon, f_c, f), \Sigma(f)] \quad (1)$$

- b. Random phase angles are computed according to a uniform distribution. At this stage it is not necessary to have time non-stationarity, thus generating random phase angles uniformly distributed is computationally more efficient.
 - c. The inverse Fourier transform is computed to obtain the simulated accelerograms.
6. A response spectrum for each realization is defined and the mean response spectrum is computed.
 7. The mean response spectrum and the target spectrum are compared to verify if they match in the short period range. If the level of matching is not satisfactory, the procedure goes back to step 5 where another k filter should be selected. The iteration continues until the desired error tolerance is achieved.
 8. Time-histories are obtained from the FAS model using the estimated ε, f_a, C and k value from the previous steps. The procedure is similar to the one described in step 5, although in this case random *logistic-distributed* phase angles (x) are computed to accomplish time non-stationarity. Logistic distribution is a normal distribution with higher kurtosis defined by a mean (μ) and a scale parameter (σ). The proposed logistic distribution has been selected since the phase derivative distributions were observed to be fat-tailed. The logistic probability density function is described by (Equation (7)).

$$f(x; \mu, \sigma) = \frac{e^{-\frac{x-\mu}{\sigma}}}{\sigma \left(1 + e^{-\frac{x-\mu}{\sigma}}\right)^2} \quad (7)$$

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The value of the mean (μ) of the distribution is not relevant in this case and thus can be chosen arbitrarily. For simplicity, μ was set equal to π/df in order to have a distribution centered around the peak. Then by simply multiplying by df it is possible to obtain the phase differences that are used to generate the phase angles. On the other hand, the scale parameter (σ) must be defined. In this work, the scale parameter was related to the effective duration (SD), which has the advantages of considering the characteristics of the entire accelerogram and defining a time frame where the ground motion is strong.²⁷ The proposed relationship between σ and SD is shown in Equation (8).

$$\log(\sigma / \pi) = \alpha_1 + \alpha_2 \log(SD) \quad (8)$$

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Different models can be used to define SD . In this work SD is considered as the sum of duration contributions dependent on magnitude (D_M), rupture distance (D_{Rrup}) and shear-wave velocity ($D_{V_{s30}}$):

$$SD = D_M + D_{Rrup} + D_{V_{s30}} \quad (9)$$

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The seismic source model of Boore (2003)⁸ describes the influence of magnitude on duration through the expression $D_M = 1 / f_c$. Atkinson and Boore (1995)²⁸ proposed a linear relation between the duration and the rupture distance: $D_{Rrup} = \beta_3 R_{rup}$. The dependence of duration on the near-surface shear-wave velocity is accounted through the following relation: $D_{V_{s30}} = \beta_4 \log(V_{s30})$.

Consequently, the relationship used to estimate the scale parameter σ becomes (Equation (10)):

$$\log(\sigma / \pi) = \alpha_1 + \alpha_2 \log[\beta_1 + \beta_2 / f_c + \beta_3 R_{rup} + \beta_4 \log(V_{s30})] \quad (10)$$

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Therefore, two steps of regression are needed. The first one is a linear regression to determine the coefficients α_1 and α_2 while the second one is a non-linear regression to define $\beta_1, \beta_2, \beta_3$, and β_4 .

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CASE STUDY AND DISCUSSION OF THE RESULTS

203 The fitted FAS model was tested using four target spectra. The first one is derived from the ground motion prediction
 204 equation (GMPE) presented by Abrahamson et al. (2014)²⁹ which is based on the NGA-West2 database.³⁰ Table 1
 205 reports the parameters that were used to calculate the geometric mean.³¹⁻³⁴
 206

207 **Table 1 - Weight coefficients used for the computation of the NGA-West2 GMPE geometric mean.**
 208

ASK	BSSA	CB	CY	IM
0.22	0.22	0.22	0.22	0.12

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 211 The other parameters for the computation of the GMPE are related to the town of Francofonte (Sicily, Italy) and are
 212 shown in Table 2.
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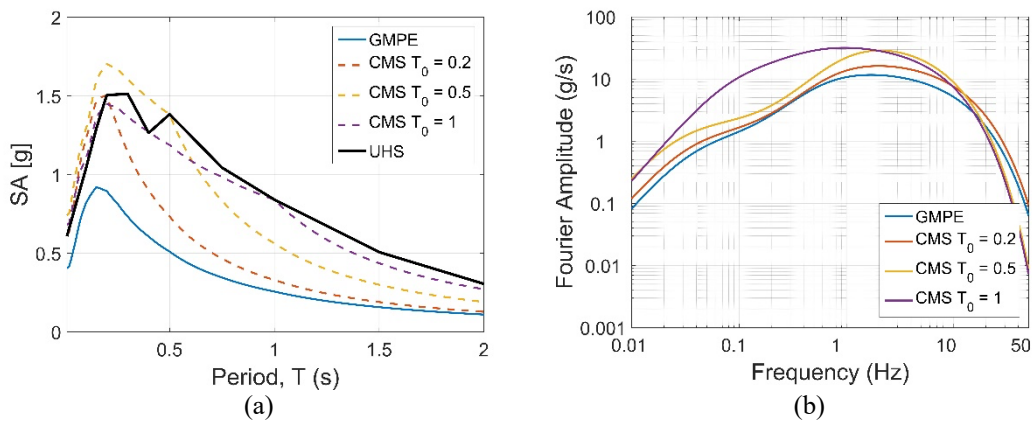
214 **Table 2 - Parameters used in GMPE computation. Omitted values are set as unknown.**
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M	R _{rup} [km]	R _{jb} [km]	R _x [km]	R _{y0} [km]	V _{s30} [m/s]	F _{rv}	F _{nm}	F _{hw}	Dip [°]	Z _{tor} [km]
7	6	4.47	-4.47	-	760	1	-	-	45	4

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 218 The GMPE was then used to compute the other three conditional mean spectra (CMS) starting from a uniform hazard
 219 spectrum (UHS) conditioned on a 2475-year return period, according to the Italian seismic hazard map. The selected
 220 structural periods for the three CMS were 0.2s, 0.5s, and 1.0s, respectively (Figure 3a). Each target spectrum was
 221 obtained as follows:

- 222 1. Calculate FAS model parameters and the *k-filter* using the procedure described in previous section. The duration
 223 of the generated signals was set to 15 s, which is about the effective duration (*SD*) obtained from the site and
 224 event parameters.
- 225 2. Generate a set of 1,000 stochastic ground motions using random logistic-distributed phase angles to obtain non-
 226 stationarity.
- 227 3. Apply a baseline correction and a Butterworth low-frequency filter with a cut-off frequency of 0.02 Hz.
- 228 4. Exclusively for CMS, remove each time-history that exceeds the mean of the target standard deviation (σ) of 2.5
 229 times. Moreover, the logarithmic standard deviation is lower bounded at 0.15 to avoid pinching phenomena in the
 230 conditioning period.
 231

232 Applying the step-by-step procedure to the Francofonte case study, it is possible to verify that the FAS models are
 233 consistent with the target spectra (Figure 3b). In particular, the 1.0 s CMS highlights the model's flexibility, as
 234 demonstrated by higher Fourier amplitudes at low frequencies.
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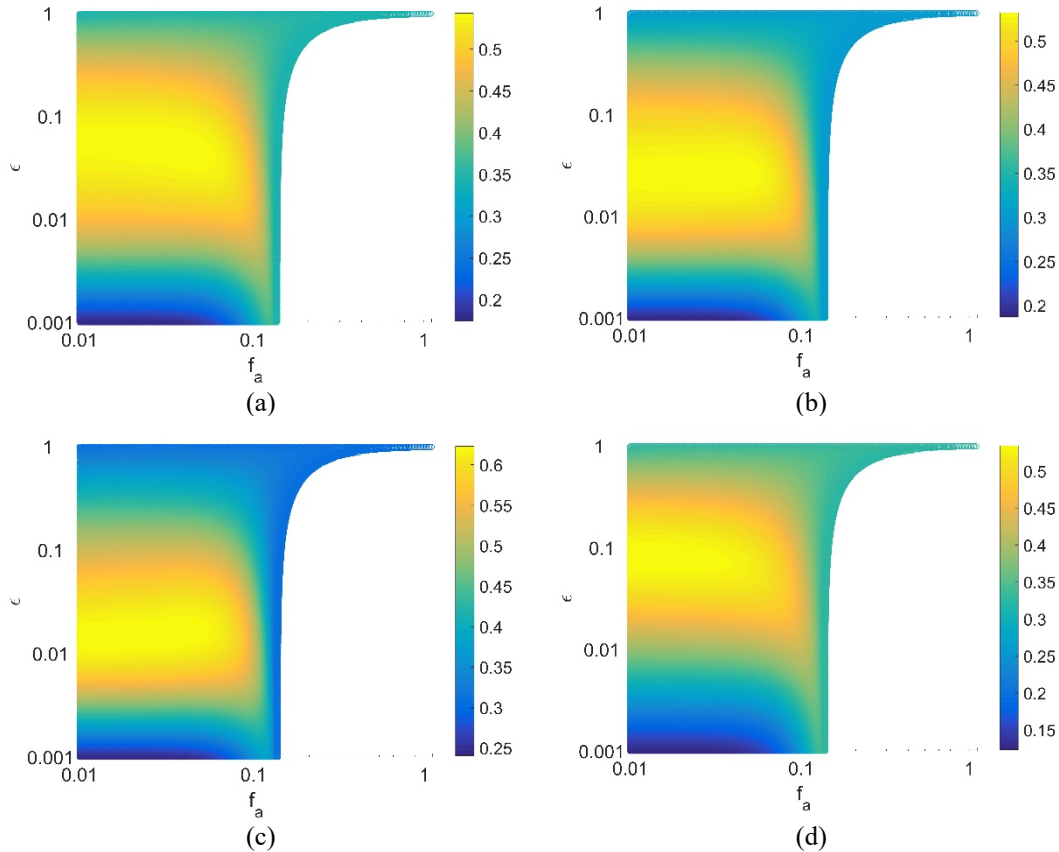
236 **Figure 3 - (a) GMPE, CMS, UHS and (b) the fitted FAS model for the Francofonte case study.**
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It is worth noting that FAS model parameters' computation includes a multivariable analysis. For each target spectrum, Figure 4 illustrates the region of possible f_a - ε pairs for a fixed C , shaded based on the coefficient of determination (R^2). As long as this case study is concerned, best pairs in terms of R^2 happen to be for ε values around 0.1, and they are far from the f_{lim} , i.e. the f_a upper bound, calculated as expressed in Equation (11).

$$f_{lim} = \sqrt{\frac{1}{1-\varepsilon}} f_c \tag{11}$$

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Figure 4 - f_a - ε solution pairs for (a) GMPE, (b) 0.2 s CMS, (c) 0.5 s CMS, (d) 1.0 s CMS.

Figure 5 shows the series of simulated spectra and their mean for each of the four target spectra. As it can be seen, the simulated mean spectrum (continuous red curve) precisely matches the target (dashed blue curve). The effect of duration in the generation of the FAS model was also investigated. The analysis was repeated considering signal durations of 10 s, 20 s, 30 s, 40 s for each of the CMS. As it can be seen from Figure 6, the duration has a limited effect on the results as the simulated spectra are all closely matching the target spectrum. The correlation coefficients (ρ) between each simulated mean spectrum and the target were also computed. The results obtained for the 10s duration seems still acceptable with a correlation coefficient of about 0.93 in the worst case (i.e., 0.2 s CMS). Increasing the duration, it is possible to notice a slight improvement of 2% in the correlation coefficients, reaching an almost perfect correlation between the simulated and the target spectrum.

A more evident demonstration of this outcome is presented in Figure 7, where the logarithmic residuals are analyzed. The continuous black line is the mean bias, whereas the light gray shading depicts the standard deviation, and the dark shading represents a 90% confidence region on the mean bias. Logarithmic residuals vary within a range of about ± 0.2 , which can be considered a solid matching.

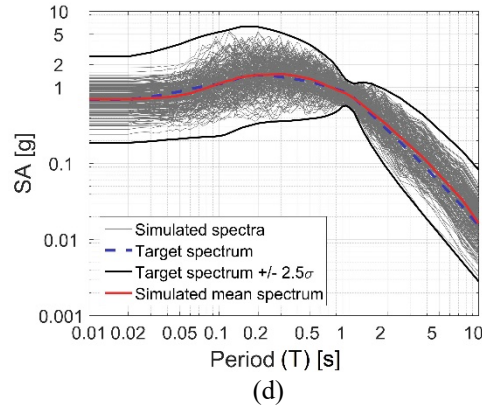
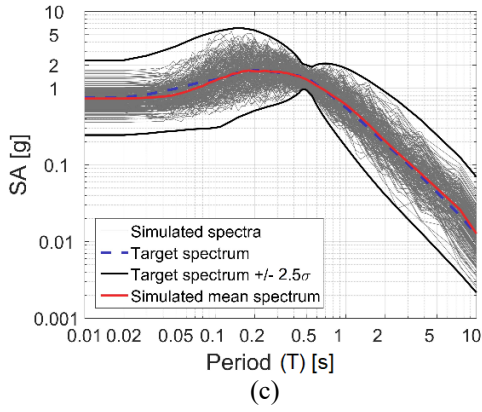
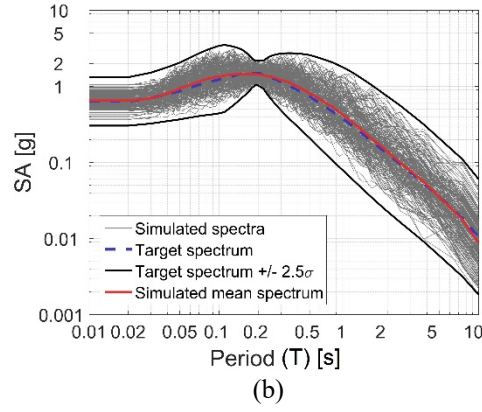
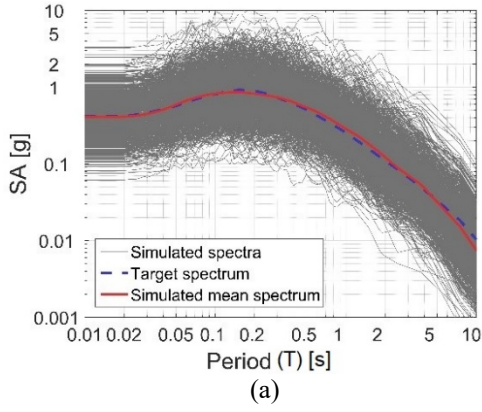
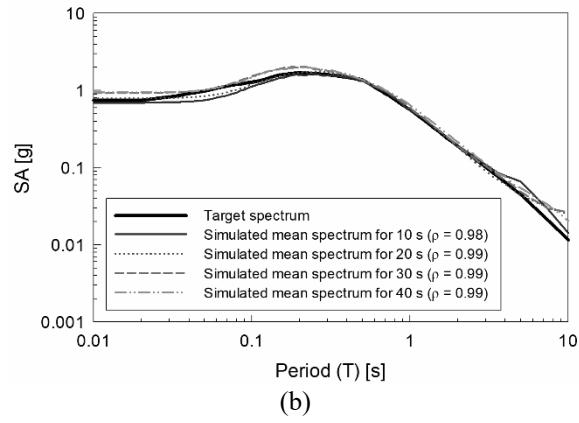
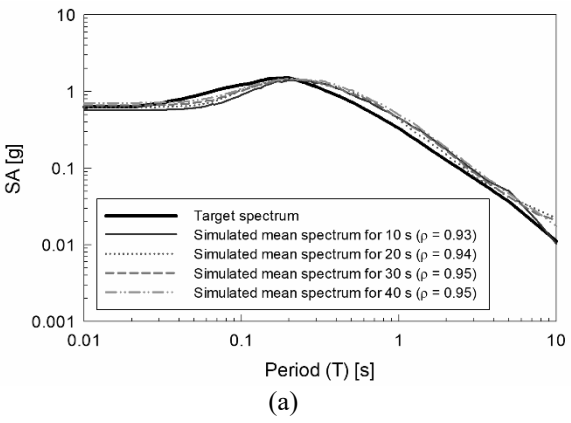
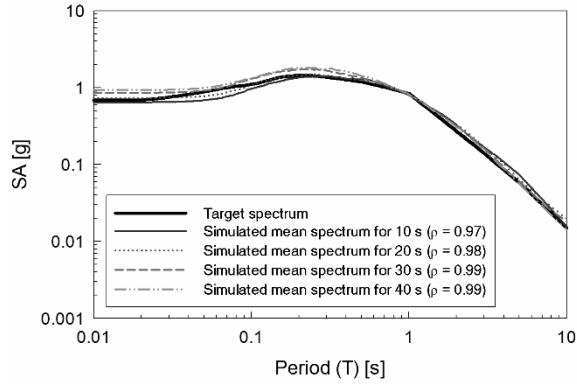


Figure 5 - Simulated spectra for (a) GMPE, (b) 0.2s CMS, (c) 0.5s CMS, (d) 1.0s CMS.

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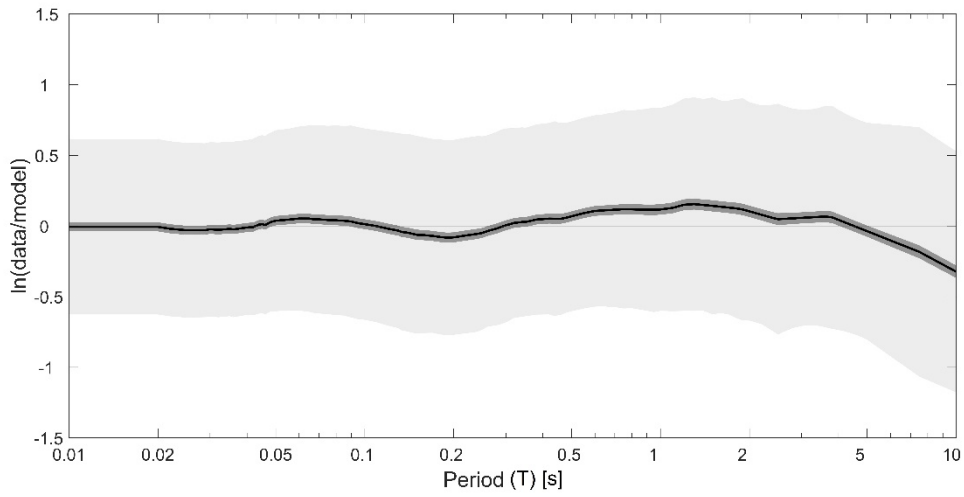




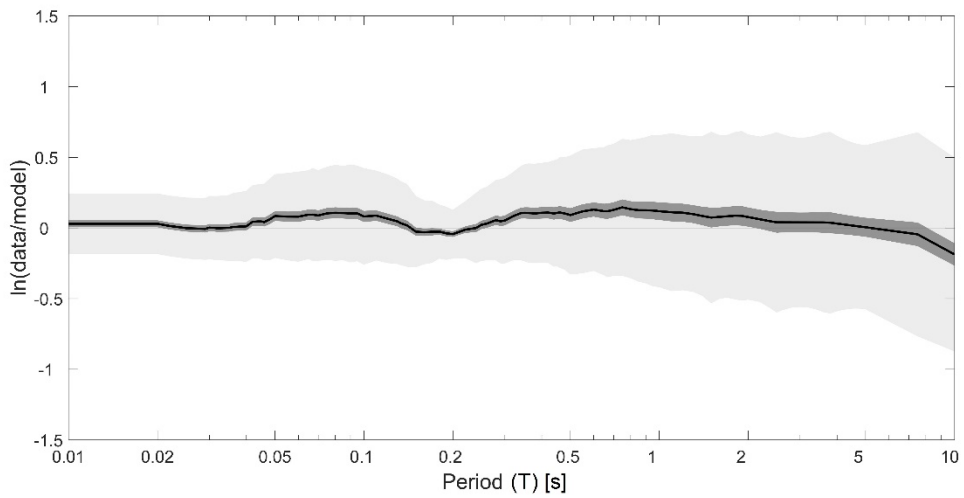
(c)

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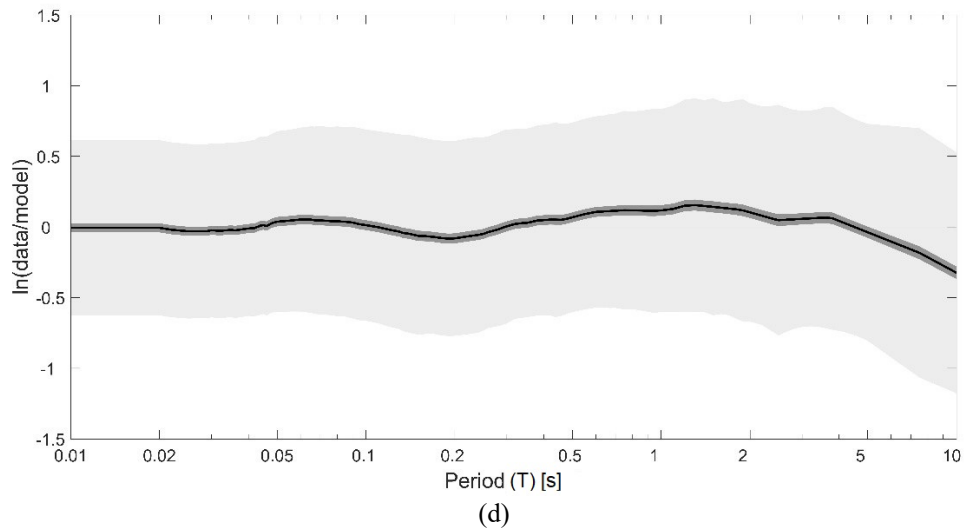
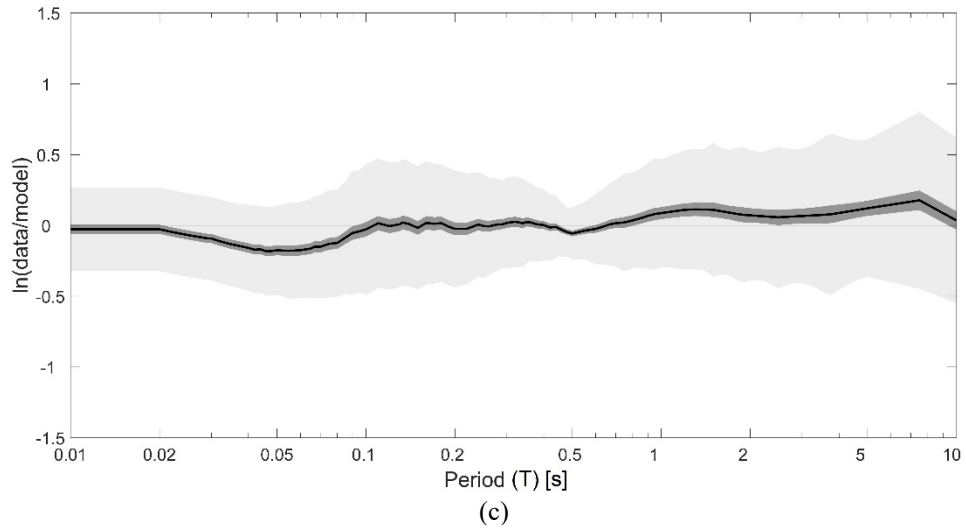
Figure 6 - Comparison of simulated mean spectra obtained for different durations for (a) 0.2s CMS, (b) 0.5s CMS, and (c) 1.0s CMS.



(a)



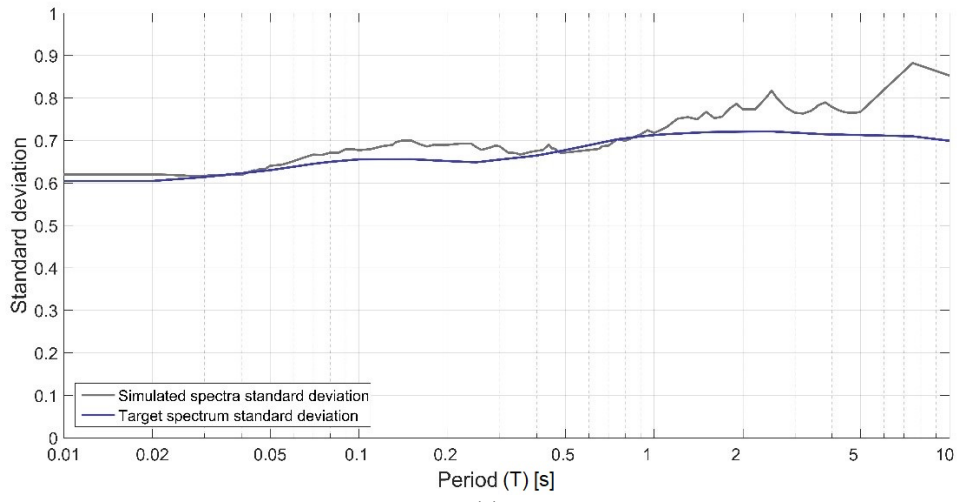
(b)



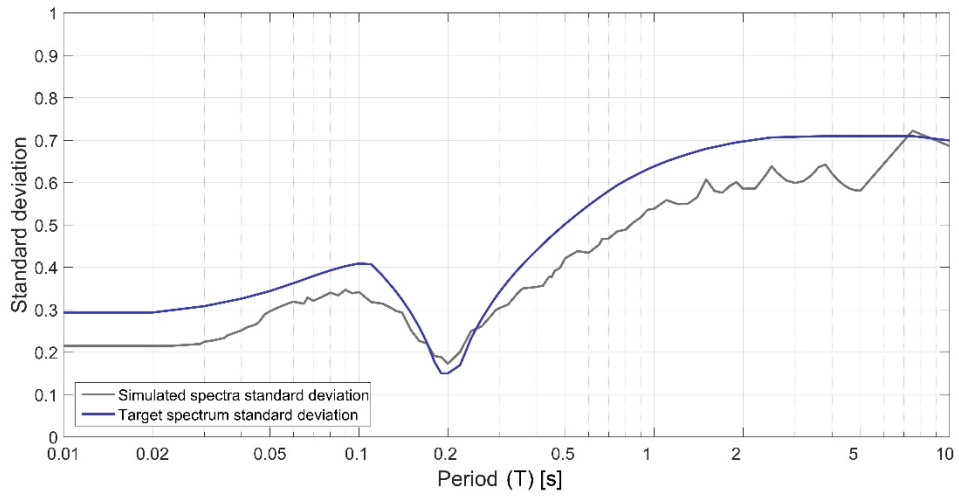
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Figure 7 - Accuracy of fitted models in terms of logarithmic residuals for (a) GMPE, (b) 0.2s CMS, (c) 0.5s CMS, (d) 1.0s CMS.

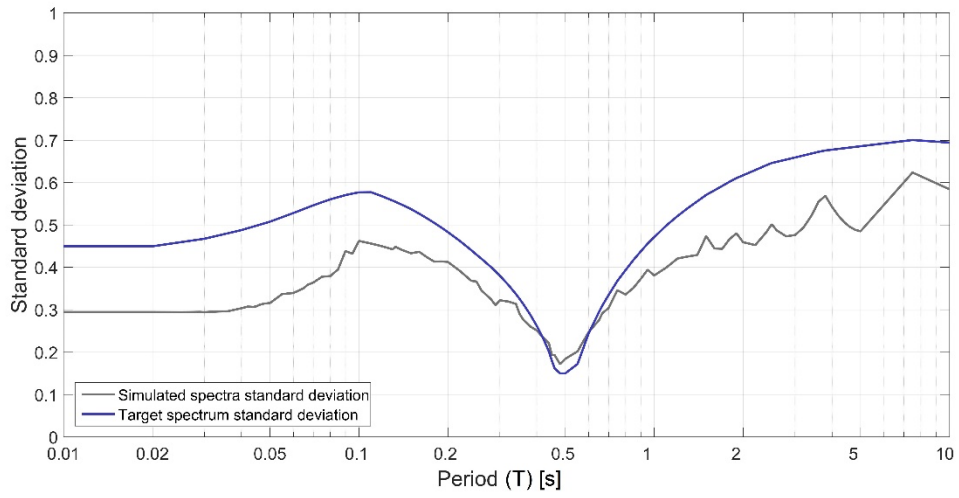
In addition, a measure of dispersion is provided comparing the logarithmic standard deviation between the target spectrum and simulated spectra. The variance in the input FAS model was assumed to be constant and equal to 0.8. This assumption allows to generate a dispersion consistent with the GMPE's standard deviation as shown in Figure 8.



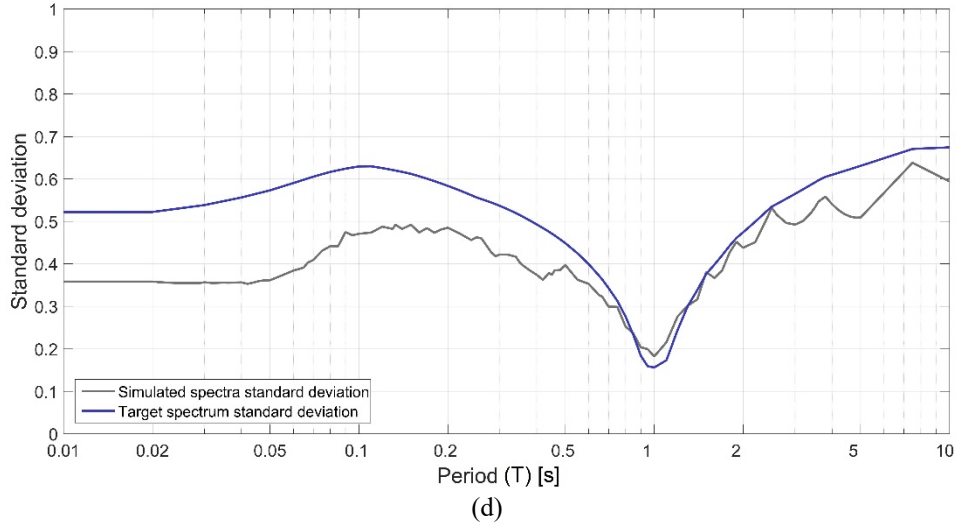
(a)



(b)



(c)



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278 **Figure 8 - Logarithmic standard deviation comparison between (a) GMPE, (b) 0.2s CMS, (c) 0.5s CMS, (d)**
279 **1.0s CMS.**
280

281 However, the comparison with CMS standard deviation pointed out an overall underestimation of the dispersion when
282 far from the corresponding conditioning period. This behavior is determined by the inter-frequency correlation model
283 implemented for the FAS generation. The model proposed by Stafford (2017)²⁶ was used in the generation of stochastic
284 ground motions. The two main terms of Equation (6) are the mean vector $FA(C, f_a, \varepsilon, f_c, f)$, and the covariance matrix
285 $\Sigma(f)$, which can be expressed as shown by Equation (12):
286

$$287 \quad \Sigma(f) = \begin{bmatrix} \sigma^2(f_1) & \rho(f_1, f_2)\sigma(f_1)\sigma(f_2) & \cdots & \rho(f_1, f_n)\sigma(f_1)\sigma(f_n) \\ \rho(f_2, f_1)\sigma(f_2)\sigma(f_1) & \sigma^2(f_2) & \cdots & \rho(f_2, f_n)\sigma(f_2)\sigma(f_n) \\ \vdots & \vdots & \ddots & \vdots \\ \rho(f_n, f_1)\sigma(f_n)\sigma(f_1) & \rho(f_n, f_2)\sigma(f_1)\sigma(f_2) & \cdots & \sigma^2(f_n) \end{bmatrix} \quad (12)$$

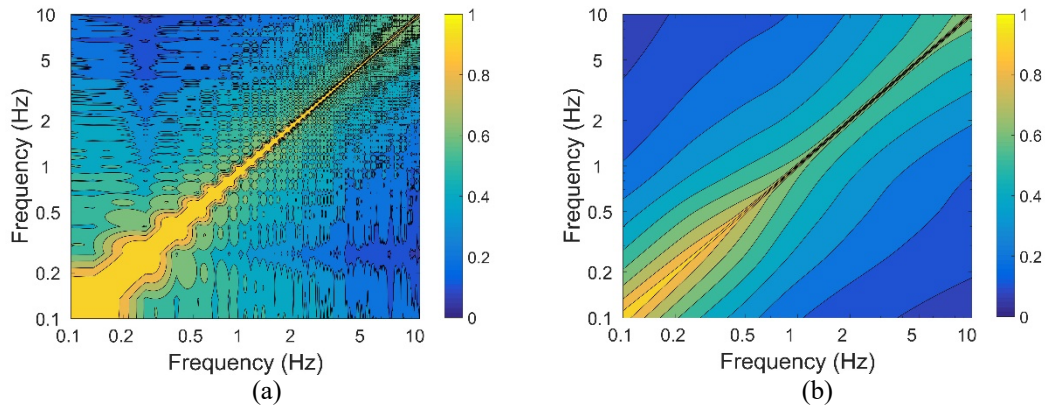
288 where $\sigma(f_i)$ is the standard deviation relative to the frequency f_i , and $\rho(f_i, f_j)$ is the correlation between f_i and f_j
289 frequencies. They depend on three different contributions: between-event component (E), within-event component
290 (A) and between-site component (S). They are explicitly calculated as indicated in Equation (13) and Equation (14).
292

$$293 \quad \rho(f_i, f_j) = \frac{\rho_E(f_i, f_j)\sigma_E(f_i)\sigma_E(f_j) + \rho_A(f_i, f_j)\sigma_A(f_i)\sigma_A(f_j) + \rho_S(f_i, f_j)\sigma_S(f_i)\sigma_S(f_j)}{\sigma(f_i)\sigma(f_j)} \quad (13)$$

$$294 \quad \sigma^2(f_i) = \sigma_E^2(f_i) + \sigma_A^2(f_i) + \sigma_S^2(f_i) \quad (14)$$

295 A test was carried out on the 1,000 simulated spectra from GMPE to check the consistency of the obtained correlation
296 and the inter-frequency correlation model.
297

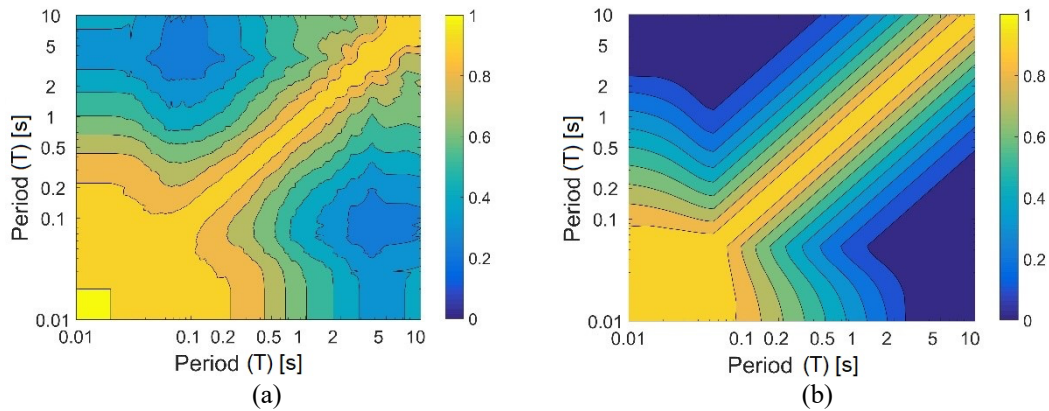
298 Figure 9a shows the correlation computed from logarithmic residuals of FAS model. Comparing this result to the
299 adopted model, it is possible to confirm the inter-frequency correlation in the FAS model (Figure 9b).
300



301
302 **Figure 9 - Correlation analysis of the FAS logarithmic residuals for: (a) the series of stochastic ground**
303 **motions and (b) the model proposed by Stafford (2017)²⁶.**
304

305 A further correlation test was performed on the spectral acceleration based on the model proposed by Baker and
306 Jayaram (2008)³⁵. A correction in the high frequencies was applied according to Carlton and Abrahamson (2014)³⁶.

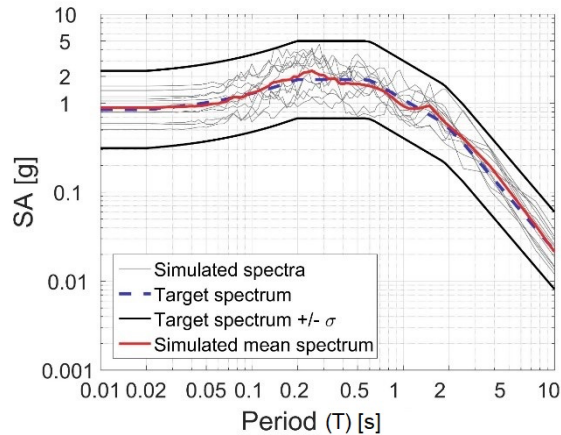
307 Figure 10 depicts the comparison between the correlation obtained from the series of the stochastic ground motions
308 and the model. Overall, it shows consistency in the shape of the two shaded regions, although overestimation is
309 detected, especially for low periods. Such difference is due to the underestimation of dispersion obtained from the
310 CMS. Therefore, the standard deviation is more correlated to the conditioning period than to the adopted model.³⁵
311



312
313 **Figure 10 - Correlation analysis of the spectral acceleration for: (a) the series of stochastic ground motions**
314 **and (b) the model proposed by Baker and Jayaram (2008)³⁵.**
315

316 The proposed methodology can also be applied to obtain a series of stochastic ground motions compatible with a
317 design spectrum. As an example, a design spectrum was calculated in accordance with the provisions of Eurocode 8³⁷
318 considering a ground acceleration (a_g) equal to 0.8g and a “C” soil category. The FAS model parameters were
319 generated through the procedure described previously. In this case a set of 50 stochastic ground motions was
320 computed, while the k filter was set to 0.08. Among these, only the simulated spectra within the range of target
321 spectrum $\pm\sigma$ were considered.
322

323 Figure 11 shows 35 simulated spectra that were selected from the set of 50 realizations. The average spectrum
324 (continuous red line) obtained from this set satisfies the spectrum compatibility required by Eurocode 8.³⁷
325



326
327
328 **Figure 11 – Example of simulated spectra matching a design spectrum calculated according to Eurocode 8.**
329

330
331 **CONCLUSIONS**
332

333 In this paper a method to obtain a Fourier amplitude spectrum model (FAS) from a response spectrum is presented.
334 Non-linear regression is used to get a FAS model from a set of white-noise samples adjusted to match the response
335 spectrum. The application of a k filter ensures the matching also in the low period region of the target response
336 spectrum.

337
338 The implemented methodology allows the generation of a series of stochastic ground motions characterized by a mean
339 value that matches a target response spectrum accurately. The time non-stationarity is achieved by including a phase
340 derivatives distribution. It could be also possible to obtain non-stationarity in the frequency content by defining a
341 function that describes the Fourier amplitude variation with time or by applying a phase derivative distribution
342 dependent on the frequency content. Furthermore, the FAS is generated by means of a covariance matrix. This leads
343 to three main advantages: (i) a dispersion consistent with the target spectrum obtained by adjusting the variance; (ii)
344 an inter-frequency correlation consistent with the seismic records; (iii) low computational effort.
345

346 The procedure has been tested on series of simulated spectra generated from a ground motions prediction equation.
347 Numerical results have shown solid matching in terms of mean and dispersion values. Further analyses demonstrated
348 how this methodology can be successfully applied also with conditional mean spectra (CMS). In addition, an inter-
349 frequency correlation model is introduced, which allows to generate an FAS with proper variability and correlation.
350 Results are consistent with the model, despite a general overestimation is observed, especially in the low period range.
351 This is potentially due to the underestimation of dispersion obtained from the CMS.
352

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354

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357 Sustainable CommUnities during Emergencies.
358

359 **DATA AVAILABILITY STATEMENT**
360

361 The data that support the findings of this study are available from the corresponding author upon reasonable request.
362

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446

447 **LIST OF FIGURE CAPTIONS**

448

449 Figure 1 - Description of the white noise generation and scaling process: (a) white noise generation; (b) Fourier
450 amplitude spectrum computation and normalization by its root mean square; (c) Fourier amplitude spectrum scaled by
451 the ω -square model; (d) time history obtained through inverse Fourier transform.

452

453 Figure 2 - (a) Adjusted response spectra and (b) Fourier amplitude spectra of the adjusted samples.

454

455 Figure 3 - (a) GMPE, CMS, UHS and (b) the fitted FAS model for the Francofonte case study.

456

457 Figure 4 - α - ϵ solution pairs for (a) GMPE, (b) 0.2 s CMS, (c) 0.5 s CMS, (d) 1.0 s CMS.

458

459 Figure 5 - Simulated spectra for (a) GMPE, (b) 0.2s CMS, (c) 0.5s CMS, (d) 1.0s CMS.

460

461 Figure 6 - Comparison of simulated mean spectra obtained for different durations for (a) 0.2s CMS, (b) 0.5s CMS,
462 and (c) 1.0s CMS.

463

464 Figure 7 - Accuracy of fitted models in terms of logarithmic residuals for (a) GMPE, (b) 0.2s CMS, (c) 0.5s CMS, (d)
465 1.0s CMS.

466

467 Figure 8 - Logarithmic standard deviation comparison between (a) GMPE, (b) 0.2s CMS, (c) 0.5s CMS, (d) 1.0s CMS.

468

469 Figure 9 - Correlation analysis of the FAS logarithmic residuals for: (a) the series of stochastic ground motions and
470 (b) the model proposed by Stafford (2017)²⁶.

471

472 Figure 10 - Correlation analysis of the spectral acceleration for: (a) the series of stochastic ground motions and (b) the
473 model proposed by Baker and Jayaram (2008)³⁵.

474

475 Figure 11 – Example of simulated spectra matching a design spectrum calculated according to Eurocode 8.