16th World Conference on Earthquake, 16WCEE 2017

Santiago Chile, January 9th to 13th 2017

Paper N° 3821

Registration Code: S-XXXXXXXX

NEW INSIGHT IN THE DERIVATION OF AMPLIFICATION FACTOR BY TAKING INTO ACCOUNT SOIL PARAMETERS

D. Zendagui[1], A. Stambouli Boudghene[2], P-Y. Bard[3], B. Derras[4]

[1] *Associate Professor, University of Tlemcen, RISAM laboratory Tlemcen Algeria, medjawad@hotmail.com*
[2] *Doctoral Research Assistant, University of Tlemcen, RISAM laboratory Tlemcen Algeria, stambouli_ahmed@yahoo.fr*
[3] *Professor, ISTerre/IFSTTAR, Université de Grenoble, Grenoble, France, Pierre-Yves.Bard@obs.ujf-grenoble.fr*
[4] *Associate Professor, University of Saida Algeria, bderras@yahoo.fr*

Abstract

It is currently admitted that the amplification factor (AF) is one of the best tools to describe site effects. AF depends on soil parameters that are derived from the geometrical and mechanical soil properties of the soil profile. Thus, it is important to identify which soil parameters shape the form of the AF. The aim of this paper is to measure the effects of various site parameters on the variation of AF. As the problem is highly complex, a tool using the GRNN (Generalized Regression Neural Network) to understand which soil parameters have been developed.

For a particular soil profile it has been found that values of AF derived from GRNN approach are closer to that of 1D linear viscoelastic seismic analysis particularly if the number of parameters increases. Based on this result a sensitivity analysis has been conducted to identify which parameters give good AF. For the practical case where we have to introduce only two parameters, it has been observed that the couple [resonance frequency (f_0) , time-averaged shear-wave velocity in the top 30 m (Vs30)] is the most interesting.

Keywords: amplification factor; site effects; soil parameters

1. Introduction

The site effects have great impact on the seismic motion and thus could cause dramatic effects on structures. For instance, during the Great Michoacan Earthquake of Mexico amplification induced by site effects has been recognized as the major cause of structural collapse [1]. After this earthquake, the classification of used sites in earthquake regulations (UBC97, EC8,…) has been increasingly based on the time-averaged shear-wave velocity in the top 30 m (Vs30). After Borcherdt [2] or many authors and engineers [3, 4], it was clear that this single parameter does not take the physics of 1D site amplification. Here important questions arise: how to define amplification factor (AF) and which parameters shape the form of this factor? Both questions have been widely addressed.
This latter is regarded as a parameter which describes site category. Other parameters such total depth, average shear wave velocity, fundamental frequency of soil, the contrast of velocity between the surface and the bedrock, profile could be used to describe site category. This has been proposed by some authors [5]. It is thus possible to combine all or some of these parameters in a unique model that is derived from a statistical treatment. However an interesting alternative to this treatment, which could be very hard to conduct especially if we want to know which parameter is the most important, is the Artificial Neural Network which has been recently used in earthquake engineering [6].

The topic of this article is to understand the effects of various site parameters on the variation of amplification factors using the GRNN (Generalized Regression Neural Network). To reach this goal a database is established in term of Amplification factor using a 1D linear viscoelastic site response analysis. It is assumed herein that the soil is multi-layered resting on a substratum. To establish this database, a set of 14 seismic acceleration has been selected and 858 profile soils have been settled.

2. Theoretical derivation of the amplification factor

2.1 General background

For a particular soil profile, the amplification factor is given as follows:

$$AF(T) = \frac{S(T)_s}{S(T)_b} \tag{1}$$

Where $S(T)_s$ and $S(T)_b$ are respectively the 5% response spectra at soil surface and reference site and T is the structural period. $S(T)_b$ is computed for a particular seismic motion whereas $S(T)_s$ is calculated using the 1D viscoelastic analysis [7] considering the following steps:

1. Choose a soil profile and a motion at substratum $b(t)$
2. Compute the Fourier transform of the motion at substratum noted $B(f)$
3. Derive the transfer function, $T(f)$ of the motion which is the ratio of motion at soil surface to the motion at substratum in the frequency domain using 1D (linear) viscoelastic analysis.
4. Compute the motion at soil surface $L(f)$ by multiplying $B(f)$ and $T(f)$
5. Perform an inverse Fourier transform on $L(f)$ to obtain the motion in time domain $l(t)$.
6. Derive the response spectra $S(T)_s$

Once $S(T)_s$ and $S(T)_b$ derived the AF could be readily obtained from Eq. (1).

2.2 Dataset

As the frequency content of the motion at the reference site will surely shape the form of the motion at the soil surface we have selected a set of motion with a large variety of frequency variety. A set of 14 seismic acceleration (S1 to S14), collected at outcropping rock, has been chosen. Both PGA and frequency content of the highest Pseudo acceleration are depicted in Table 1.

Table 1 – PGA for the 14 acceleration time histories

Identification	PGA (m/s²)	Frequency content of the highest PSA
S1	1.269	f<2Hz
S2	1.288	f<2Hz
S3	3.190	f<2Hz
S4	2.074	2Hz<f<4Hz
S5	3.106	2Hz<f<4Hz
S6	3.140	2Hz<f<4Hz
S7	1.0030	4Hz<f<8Hz
S8	1.4740	4Hz<f<8Hz
S9	3.0060	4Hz<f<8Hz
S10	1.4960	4Hz<f<8Hz
S11	1.023	8Hz<f<16Hz
S12	4.260	8Hz<f<16Hz
S13	1.393	8Hz<f<16Hz
S14	0.803	8Hz<f<16Hz

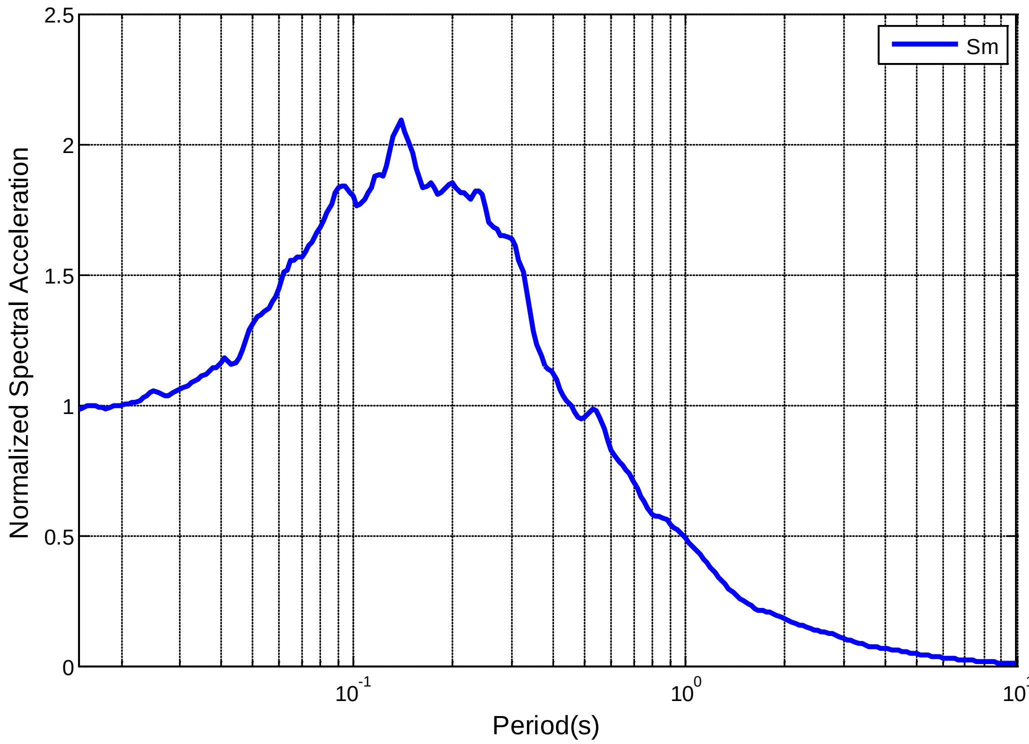


Fig. 1 – 5% Geometrical mean of the normalized damped response spectral acceleration $S(T)_b$

It is worth noting that values of the PGA covered a wide range of excitation ranging between 0,08g and 0,42g. Also, the 14 excitation are characterized by a various frequencies. Indeed the 5% Normalized damped response spectral acceleration for a set of seismic acceleration (S1 to S14) collected at substratum shows that the frequency content varies from 0,1Hz to 100 Hz. Fig. 1 shows the variation of the geometrical mean of the normalized damped response spectral acceleration.

2.3 Soil classification and derivation of site parameters

A total of 858 profiles has been selected. The site parameters that define site category have been selected as: depth(D), average shear velocity (v_{sm}), average shear wave velocity at the upper 30m (v_{s30}), shear wave velocity in the substratum (v_{n+1}), contrast of velocity Cv) and fundamental frequency of soil profile. They are defined as follow:

$$D=\sum_{m=1}^{n} h_m \tag{2}$$

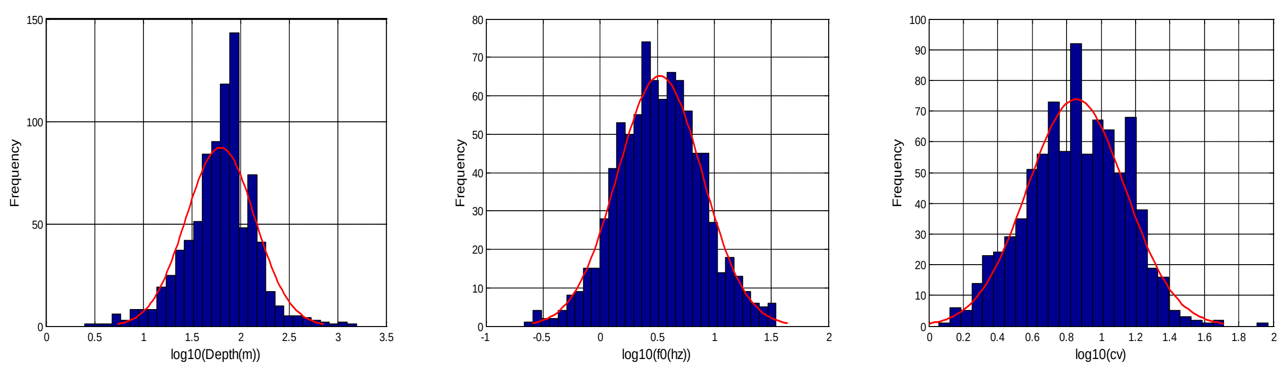
$$V_{sm}=\sum_{i=1}^{n} h_m \Big/ \sum_{i=1}^{n} \frac{h_m}{v_m} \tag{3}$$

Where $v_m=\sqrt{G_m/\rho_m}$ is the shear wave velocity in layer (m)

$$V_{s30}=30 \Big/ \sum_{m=1}^{N30} \frac{h_m}{v_m} \tag{4}$$

$$Cv=\frac{v_{n+1}}{v_1} \tag{5}$$

(where N30 is the number of layers in the topmost 30 meters)
The fundamental frequency (f_0) of soil profile is determined through the simplified version of the Rayleigh procedure [8]. Thus for each profile, a set of six parameters have been calculated. The logarithm distributions of these parameters follow a normal distribution (Fig. 2).



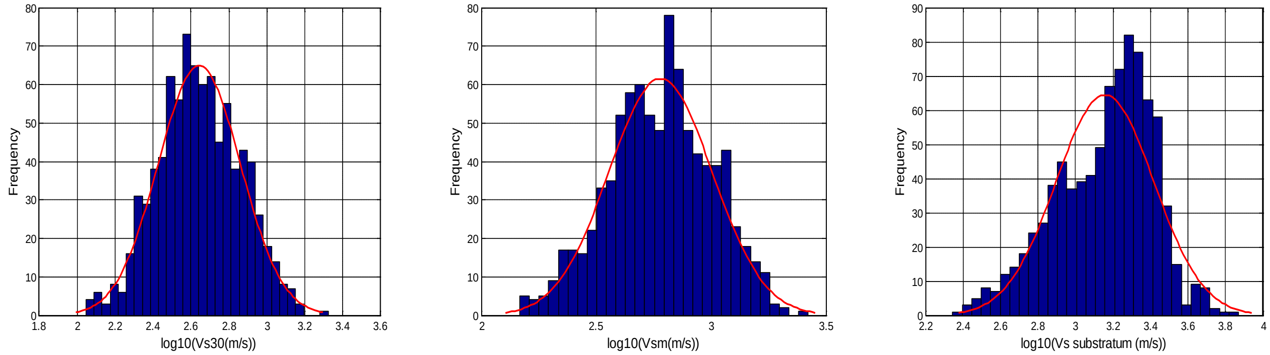


Fig. 2 – Distribution of the site parameters

The 858 profiles have various values of the velocity at substratum. In order to compare results obtained for these profiles the velocity at substratum is normalized such that all profiles rest on a substratum with an equal shear wave velocity equal to 800 m/s. Such a velocity scaling is performed to keep unchanged the site fundamental frequency, so that the new site parameters for these normalized profiles are now:

- Normalized depth of the profile

$$D' = \left(\frac{800}{v_{n+1}}\right) * D \tag{6}$$

- Normalized average shear wave velocity

$$v'_{sm} = \left(\frac{800}{v_{n+1}}\right) * v_{sm} \tag{7}$$

- Normalized average shear wave velocity at the upper 30m

$$V'_{s30} = \frac{30}{\sum_{m=1}^{N'_{30}} \frac{h_m(800/v_{n+1})}{v_m(800/v_{n+1})}} \tag{8}$$

The contrast of velocity and fundamental frequency of soil profile doesn't change while performing normalization, while the total thickness D', the average velocity V'sm and the avrerage V'_{S30} are changing because of the thickness or velocity changes.

2.4 Description of the database elaborated in terms of Amplification factor (AF)

The AF (Eq. (1)) has been calculated for the 2x858 profiles (normalized and not normalized soil) subjected to 14 seismic excitations. Thus the database is constituted of 2x858x14=24024 AF. The AF depends on: soil profile (either normalized or not normalized) and excitation at substratum. Thus it is written $AF(P_k, \theta, S_l, T_i)$ where

P_k, $k = 1, \ldots 858$ is introduced to identify the soil profile,

$\theta = 1$ for not normalized soil profile, $\theta = 0$ for normalized soil profile

S_l, $l = 1, 14$ is the l^{th} excitation. Note that if l=m its means that the geometrical mean of the fourteen excitation is used.

T_i, $(i = 1, ..271)$ is the i^{th} structural period. The 271 values are log equally spaced between 0,01s and 10s.

Once the AF calculated for a particular profile, let say k, and for the 14 seismic excitation, the geometrical mean of AF are then deduced as follow

$$log[AF(P_k,\theta,T_i)] = (\frac{1}{14})\sum_{l=1}^{14} log[AF(P_k,\theta,S_l,T_i)] \quad (9)$$

Hereafter $AF(P_k,\theta,T_i)$ stands for AF. Some new parameters are introduced to measure the variability of the results.

- Means of AF

$$log\big(A_1(\theta,T_i)\big) = \frac{1}{n_p}\sum_{k=1}^{n_p} log[AF(P_k,\theta,T_i)] \quad (10a)$$

Where n_p is the total number of profile.

- Variability error

$$Ve_1(\theta,T_i) = \sqrt{\frac{1}{n_p}\sum_{k=1}^{n_p}[\log(AF(P_k,\theta,T_i)) - \log(A_1(\theta,T_i))]^2} \quad (10b)$$

- Max of the variability error

$$MVe_1(\theta) = max[Ve_1(\theta,T_i)] \quad (10c)$$

- Total variability error

$$TVe_1(\theta) = \frac{1}{n_T}\sum_{i=1}^{n_T} Ve_1(\theta,T_i) \quad (10d)$$

Where n_T is the number of structural period or frequency used.

2.5 Means and variability of the AF

For profiles which are not normalized we compute the 12012 AF and derived the mean of amplification factor and (mean± variability of error) (Fig. 3). The various variability at different value of the period are presented in Table 2.

Table 2 – Derivation of the variability parameters

Variability total of error (in log10)	0.1178
Max variability of error (in log10)	0.1717
Variability of error (in log10)at (t=0.01s)	0.1227
Variability of error (in log10)at (t=0.02s)	0.1226
Variability of error (in log10)at (t=0.04s)	0.1206
Variability of error (in log10)at (t=0.07s)	0.1314
Variability of error (in log10)at (t=0.1s)	0.1494
Variability of error (in log10)at (t=0.2s)	0.1623
Variability of error (in log10)at (t=0.4s)	0.1446
Variability of error (in log10)at (t=0.7s)	0.1200
Variability of error (in log10)at (t=1s)	0.1040
Variability of error (in log10)at (t=2s)	0.0626
Variability of error (in log10)at (t=4s)	0.0477
Variability of error (in log10)at (t=7s)	0.0388
Variability of error (in log10)at (t=10s)	0.0412

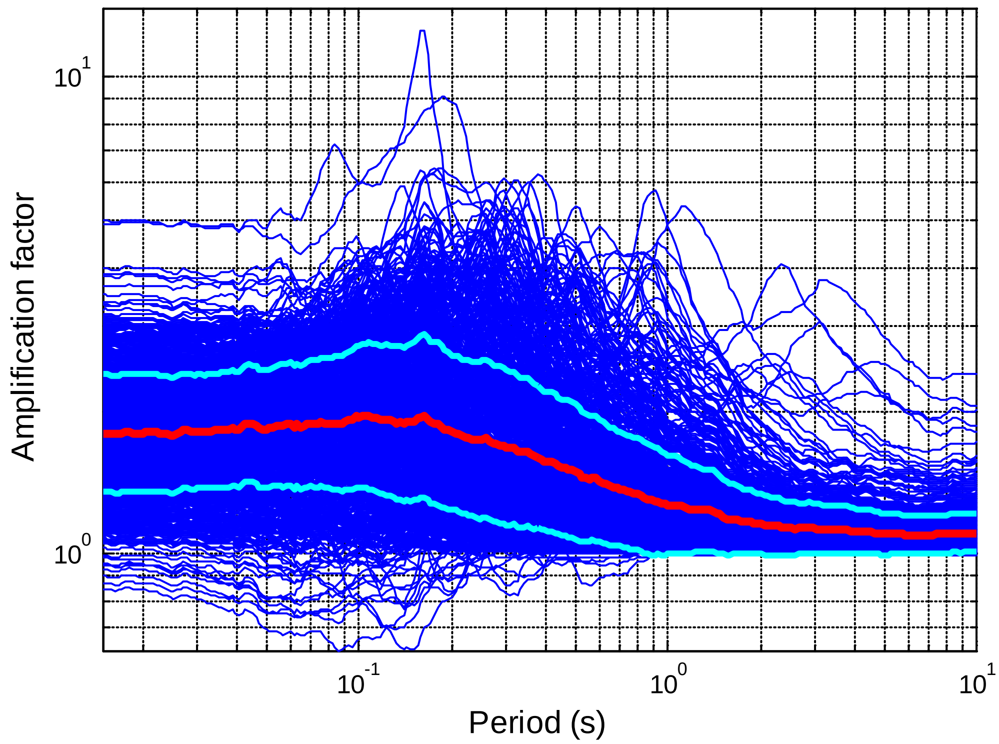


Fig. 3 – The AF for each profile, mean of amplification factor (red line) and mean ± variability error(bright blue line)

The database in term of AF has been constituted either for normalized or not normalized soil profile, which are widely used to describe site effects, have been assessed. The main issue now is to understand how site parameters shape the form of both AF . To reach this goal we have used a newly neural network approach called GRNN. Next section will be dedicated to a description of GRNN approach.

3. Derivation of the AF using the neural network appraoch

The GRNN is a pattern of the neuron networks at radial basis network (RBF) [9]. It is based on networks of kernel regression [10, 11] where the desired function is reached by a linear combination of the appropriate Gaussian functions. The GRNN is composed of four layers: the entry layer, the pattern layer, the summation layer and the exit layer. The foreseen value y'i, is defined as follow by [12]:

$$y_i^{'} = \frac{\sum_{i=1}^{Q} y_i * \exp(-D(x, x_i))}{\sum_{i=1}^{Q} \exp(-D(x, x_i))} \tag{11a}$$

with :

$$D(x, x_i) = \sum_{k=1}^{R} \left(\frac{x_k - x_{ik}}{\sigma} \right)^2 \tag{11b}$$

X_k : The entry vector of the k line.
x_{ik} : The learning vector between the i^{th} neuron of the hidden layer and the entry vector of the K line.

σ: the Gaussian width.
Q: is the number of vectors submitted to the learning.
R: is the element number of the entry vector (the site parameters).

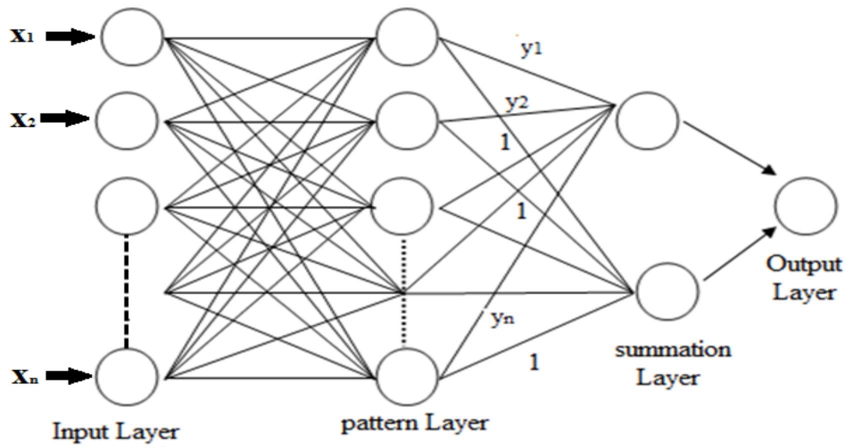


Fig. 4 – The general structure of the GRNN method

4. Results and discussion:

4.1 General schemes

The database is constituted of 858 profiles either normalized or not for which we calculated AF in terms of period and normalized frequency. Thus the sensitive analysis will be conducted for six schemes. In turn, the soil profiles are fully identified by its site parameters. It is worth noting that 75 % of the database has been used in the training phase whereas 25% has been used in the test phase.

4.2 Comparisons between AF deduced from GRNN and analytical model

This part shows that values of AF deduced through GRNN are close to that obtained in the database. The standard deviation tends to increase as number of parameters decreases (Table 3). It is worth noting that for a particular soil profile (see soil parameters Table 4) which is one of the 858 profiles, we found that GRNN gives value of AF close to the analytical model (Fig. 5).

In order to measure the robustness of the approach we compute the AF for a soil profile that is not in the database (see soil parameters Table 5). Careful examination of the results (Fig. 6) shows that values AF factors from GRNN tend to be different from that of the database as the number of soil parameters decreases.

Obviously the difference between these values depends on the soil profile. Thus it is important to derive the error in terms of standard deviation for both period obtained for normalized and not normalized soil profile. The results obtained are depicted in section 4.3.

Table 3 – Standards deviation with variation of the number of site parameters.

Number of parameters	Description of the parameters	Standard deviation	R=1-(sigma model/sigma original data)
All parameters	Depth+ f_0+ v_{sm} + Cv +V_{s30}+ V_{n+1}	0.0011	0.99066

Three parameters	$f_0 + Cv + V_{s30}$	0.0079	0.93293
Two parameters	$f_0 + Cv$	0.0251	0.78692
Two parameters	$f_0 + V_{s30}$	0.0782	0.33616
One parameter	Cv	0.0725	0.38455
One parameter	V_{s30}	0.1038	0.11884

Table 4– Soil parameters of a soil profile that belong to the database.

Depth (m)	f_0 (Hz)	V_{sm} (m/s)	Cv	V_{s30} (m/s)	V_{n+1} (m/s)
49.00	4.15	552.47	10.45	455.93	2300

Table 5 – Soil parameters of a soil profile that is not from to the database.

Depth (m)	f_0 (Hz)	V_{sm} (m/s)	Cv	V_{s30} (m/s)	V_{n+1} (m/s)
102.00	3.34	780.09	10.00	347.93	2500

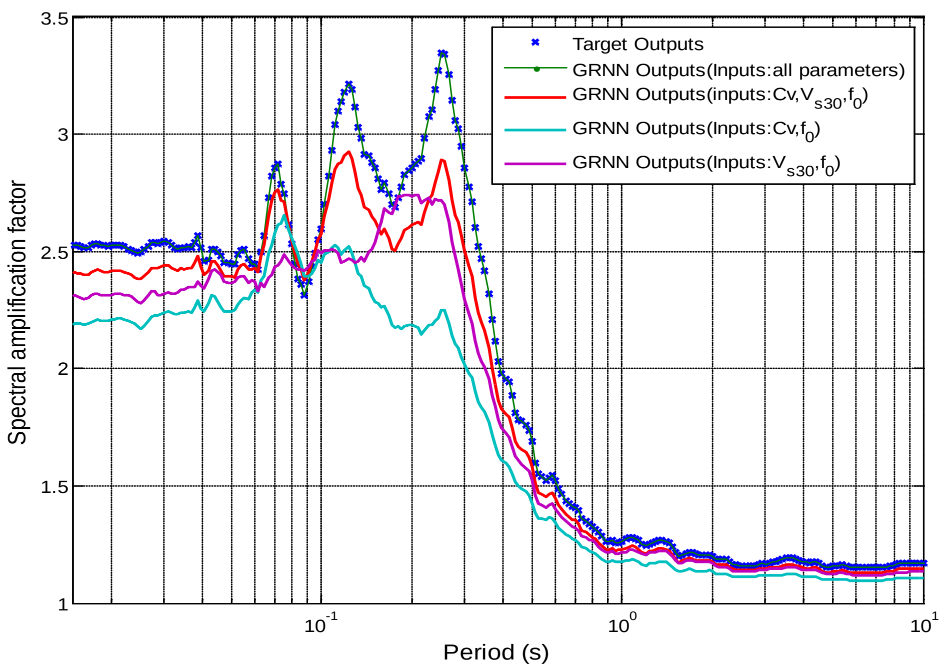


Fig. 5 – Comparison of AF obtained by various GRNN models with the actual AF obtained by 1D simulation, for a soil profile included in the model database

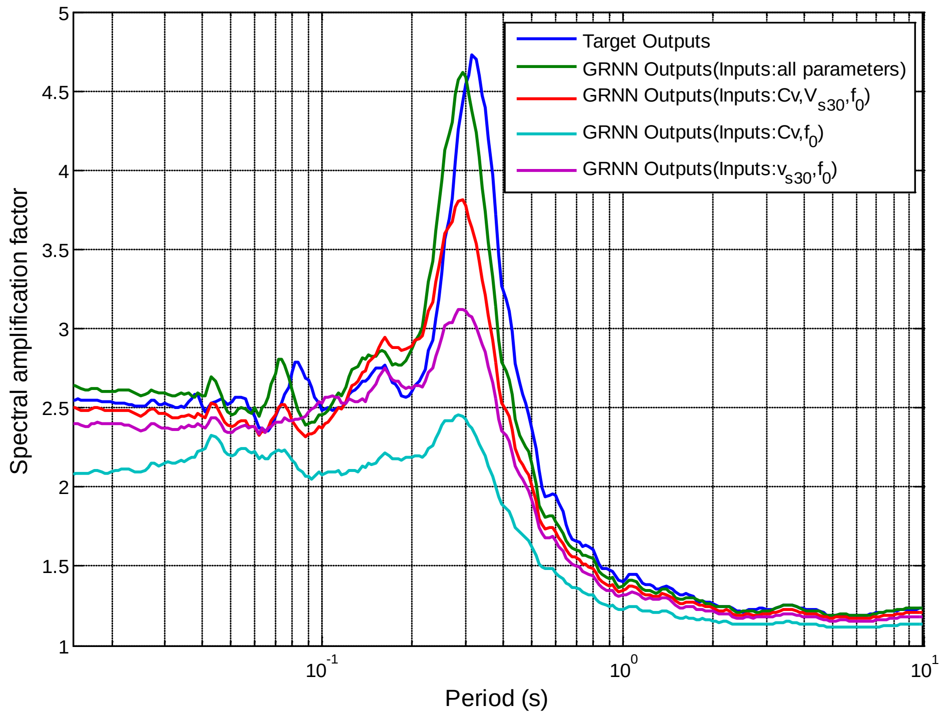


Fig. 6 – Comparison of AF obtained by various GRNN models with the actual AF obtained by 1D simulation, for a soil profile that is not from to the database

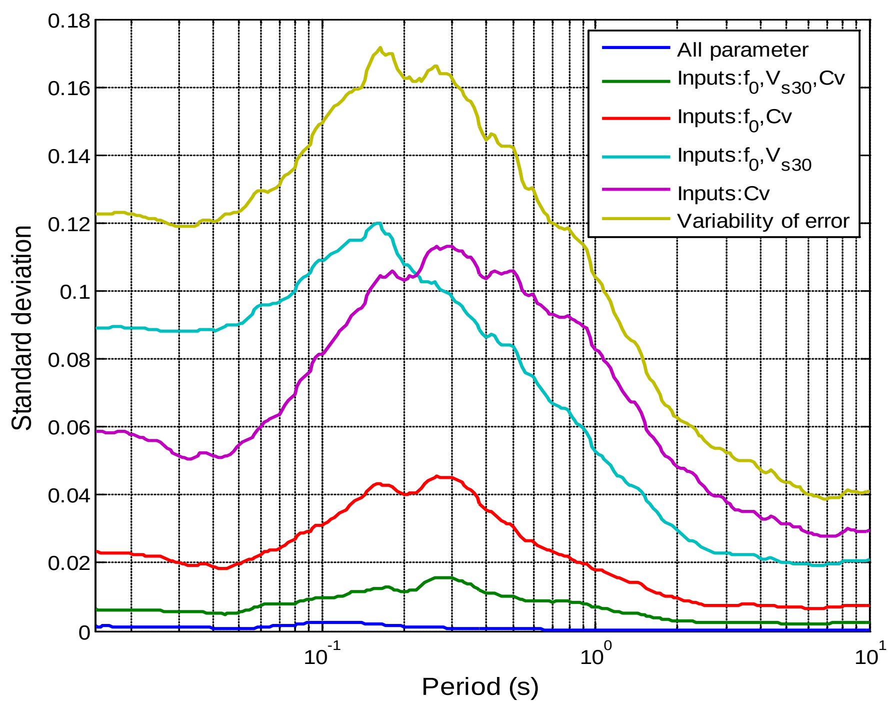


Fig. 7 – Standard deviation of AF deduced by GRNN and analytical model for original soil profiles (with varying bedrock velocities)

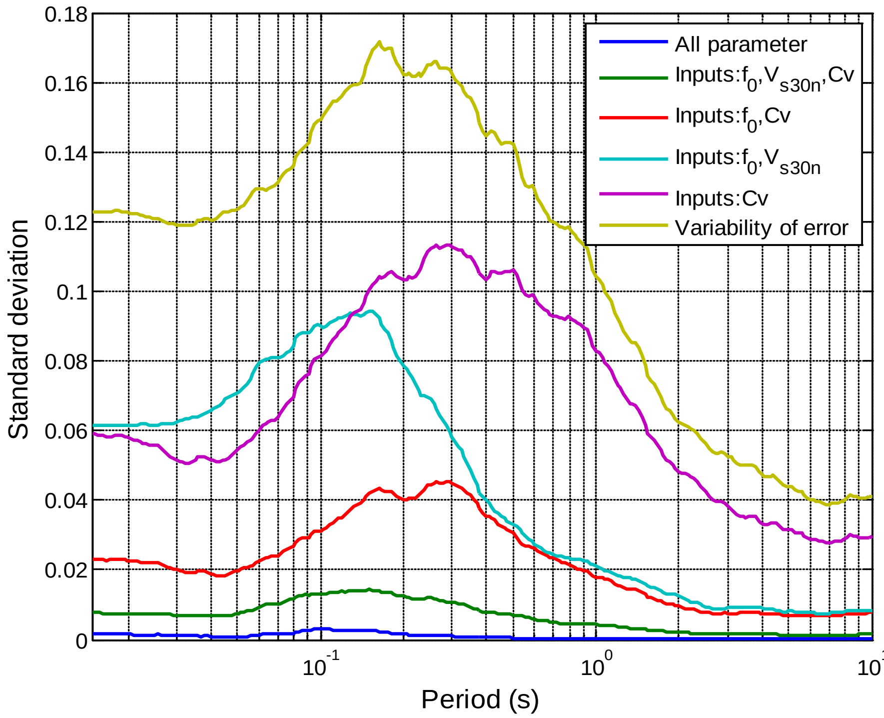


Fig. 8 – Standard deviation of AF deduced by GRNN and analytical model for soil profile normalized at a bedrock velocity of 800m/s

4.3. Derivation of standard deviation for various case

We have derived the standard deviation for various cases (Figs 7-8). It is important to note that the difference between values of AF from GRNN and analytical model tend to decrease as the number of soil parameters increase. However for practical reason it is more interesting to introduce a small number of soil parameters. This study shows that if we try to use only two parameters the best combinations is f_0, *Cv*. However, engineers experience difficulty to determine values of *Cv* and as far as the results of this study shows, it is preferably to use the combination of f_0 and vs_{30}. This combination leads to acceptable values of standard deviation.

5. Conclusion

Site effects have a great impact on the seismic motion and thus could cause dramatic effects on structures. These effects are generally described in seismic regulation codes by simple coefficients which are in turn based on amplification factors (AF). The latter are derived using soil parameters. This paper attempts to address the problem on how these soil parameters control the frequency dependent shape of AF. To reach this goal a database in term of AF is established by considering a 1D, linear viscoelastic seismic analysis. Using the GRNN (Generalized Regression Neural Network), it has been found that values of AF derived from GRNN approach get closer to that of 1D viscoelastic seismic analysis when the number of site parameters considered in the GRNN model increases. Based on this result a sensitivity analysis has been performed to identify which parameters provide satisfactory estimates of AF. For the practical case where we have to use only two parameters, which should in addition be easily available in the field, it has been observed that the couple (f_0, V_{S30}) (i.e., fundamental frequency shear + average wave velocity over the upper 30m) is the most interesting compromise between affordability and accuracy.

This prelimanry study has been performed here only in the linear viscoealstic domain, and should be extended to non-linear site response: in such a case, it will be necessary to consider somme additional input parameters, basically for the loading level (i.e., PGA or PGV), and for the soil type (i.e., cohesive or cohesionless, or plasticity index), which are essential for NL behavior.

6. Acknowledgements

This study is supported by the Direction Générale de la Recherche Scientifique et du Développement Technologique (DGRSDT) Algiers Algeria through RISAM laboratory, ISTERRE laboratory and the project 13MDU901 supported by Tassili program. Authors wish to acknowledge these supports.

7. References

[1] Bard PY, Campillo M, Chavez-Garcia FJ, Sanchez-Sesma FJ (1988): The Mexico earthquake of September 19, 1985-A theoretical investigation of large-and small-scale amplification effects in the Mexico City Valley. *Earthquake Spectra*, **4** (3), 609-633.

[2] Borcherdt RD (1994): Estimates of site dependent response spectra for design (methodology and justification). *Earthquake Spectra*, **10** (4), 617-653.

[3] Castellaro S, Mulargia F, Rossi PL (2008): Vs30: Proxy for Seismic Amplification? *Seismological Research Letters*, **79** (4), 540-543.

[4] Mucciarelli M, Gallipoli MR (2006): Comparison between Vs30 and other estimates of site amplification in Italy. *1st First European Conference on Earthquake Engineering and Seismology*, Geneva, Switzerland.

[5] Cadet H, Bard PY, Duval AM (2008): A new proposal for site classification based on ambient vibration measurements and the kiknet strong motion data set. *14th World Conference on Earthquake Engineering*, Beijing, China.

[6] Derras B., Bard PY, Cotton F, Bekkouche A (2012): Adapting the neural network approach to PGA prediction: an example based on the KiK-net data. *Bulletin of the Seismological Society of America*, **102** (4), 1446–1461.

[7] Kramer SL (1996): *Geotechnical earthquake engineering*. Pearson Education India.

[8] Dobry R, Oweis I, Urzua A (1976): Simplified procedures for estimating the fundamental period of a soil profile, *Bulletin of the Seismological Society of America*, **66** (4), 1293-1321.

[9] Wasserman PD (1993): *Advanced Methods in Neural Computing*. Wiley.

[10] Kim B, Lee DW, Parka KY, Choi SR, Choi S., (2004). Prediction of plasma etching using a randomized generalized regression neural network, *Vacuum*, **76** (1), 37–43

[11] Cigizoglu HK, Alp M (2005): Generalized regression neural network in modeling river sediment yield. *Advances in Engineering Software*, **76** (1), 63–68.

[12] Specht DF (1991): A general regression neural network. *Neural Networks, IEEE Transactions on*, **2** 6), 568-576.