Neuronal Approach and the Use of KIK-NET Network to Generate Response Spectrum on the Surface

Boumédiène Derras [1], Abdelmalek Bekkouche [2] and Djawad Zendagui [3]

[1] Department of Civil Engineering, Moulay Tahar University, Saïda, Algeria, E-mail: b_derras@mail.univ-tlemcen.dz
[2], [3] Department of Civil Engineering, Faculty of Engineering, Abou Bekr Belkaïd University, 13000 Tlemcen, Algeria,
E-mail: a_bekkouche@mail.univ-tlemcen. dz.; E-mail: d_zendagui@mail.univ-tlemcen.dz

ABSTRACT

The determination of response spectrum of a seismic excitation recorded on a chosen site is necessary in the structural dynamic design. The response spectrum can be obtained directly from recorded seismic data but this operation is expensive. The aim of this work is to avoid this problem where the acceleration response spectrum at the free face of a classified site is generated from that of reference by using the method of Artificial Neural Networks (ANN). The recorded spectrum value and corresponding period represent the inputs of the RNA, while the output is only the spectrum response value on the free field. The seismic data and the sites of the KIK-NET accelerograph network are used for the training and the validation of the neuronal model. The promising results obtained by this approach open a new research orientation on the use of the ANN in the field of soil dynamics and signal treatment, thus allowing the enrichment of the paraseismic codes into force.

KEYWORDS: Site effect, Artificial neural networks, Acceleration response spectrum, Seismic data, Soil dynamics.

INTRODUCTION

Any construction obeys standard rule codes. These last represent a platform on which the engineer can find solutions to problems such as earthquakes threatening the human life. The most common method usually used for the structural dynamic calculation (and which is also used in paraseismic code of Algerian RPA) is based on the definition and the use of the response spectrum. However, the exact determination of the response spectrum of seismic vibration in a given site requires the deployment of accelerographs and a certain number of *in situ* tests to know the mechanical characteristics of the site (Vincenzo et al., 2007).

To minimize the costs and to reduce the deadlines, obtained information of the dense networks of accelerographs installed all over the world can be developed by an approach based on the neuronal method. The latter was largely used successfully and is perceived like an effective tool of modeling in various fields (Juan et al., 2006). The neuronal methods make it possible to estimate the response spectrum in acceleration for various types of soil and thus to deduce the risk related to the effect of site.

In the present work, the neural network of the multi-layer Perceptron type, with the rule of Widrow-Hoff for the training and the data of the network of accelerographs KIK-NET were used for the simulation of response spectrum on the surface. Stations "KIK-NET" are equipped with two accelerographs, the first on the surface and the second in-depth (Guillaume Pousse, 2006; Shin et al., 2004). The great depth, where the stations are anchored, represents the advantage of the purity of information: nonaffected by the phenomena of surface; what has made it possible to analyze seismic amplification in its true size. The inputs of the neuronal system are: In-depth recorded spectral acceleration and the corresponding period. The output is the spectral acceleration recorded on the free surface of the ground.

Accepted for Publication on 15/1/2010.

ARTIFICIAL NEURAL NETWORKS

These past years, the artificial neural networks knew an interest growing by the scientific community in the seismic field of engineering. This importance extends as an example on the estimation of risk related to effect of 1-D site (Bekkouche et al., 2005) or 2-D (Paolucci et al., 2000), on the generation of the accelerogrammes compatible to response spectrums (Ghaboussi et al., 1998; Chu-Chieh et al., 2001), on the estimation of an artificial earthquake and the response spectrum (Seung et al., 2002), on the determination of the maximum seismic acceleration of the soil (Tienfuan et al., 2005) and on the evaluation of the liquefaction potential (Goh, 1994). An artificial neuron is a very simple mathematical operator, having inputs which can be the output of other neurons, input of external signals or an output. The value of the output results from the calculation of the sum of the inputs, balanced by coefficients (known as weights of connections or synaptic weights) and the calculation of a function (known as function of activation) of this balanced sum.

The functions of activation often used are either the identity function f (x) = x whose neurons are called linear neurons or a non-linear one like the hyperbolic tangent f (x) = tanh(x), and it is a continuous function, differentiable and limited.

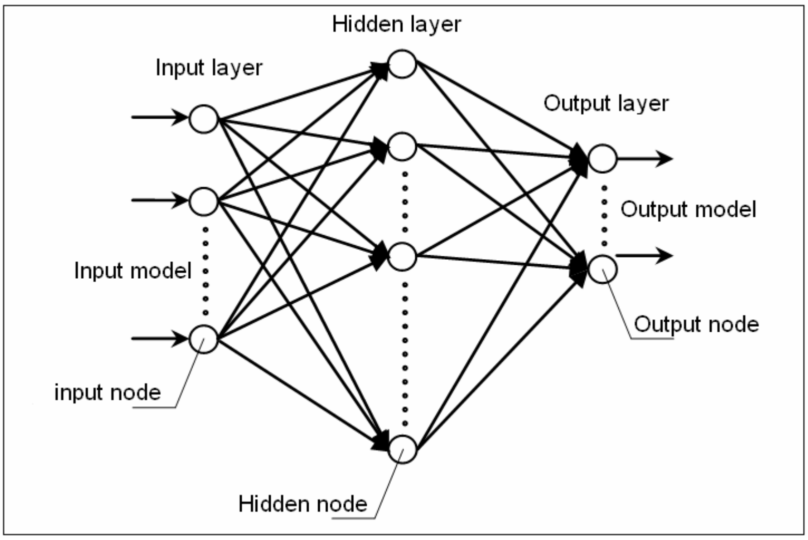


Figure 1: Neural network of multi-layer perceptron type

Multi-Layer Perceptron (MLP)

The MLP has a quite particular structure. Its neurons are organized in successive layers (Figure 1), each neuron of a layer receives signals of the preceding layer and transmits the result to the following one, if it exists. The neurons of the same layer are not inter-connected and thus a neuron can send its result only to a neuron located in its posterior layer (Yu et al., 2002).

Training of the MLP

The training of these networks is supervised. The algorithm used during this training is known as method of retropropagation of the gradient (Herve, 1994). This method of training is divided into two stages. The first is a phase of propagation, which presents a configuration of inputs to the network to propagate these inputs gradually to next ones until the output layer is passed by the hidden layers. The second is a phase of retropropagation, which consists, after the process of propagation, to minimize the error made on the whole of the examples presented. This error represents the sum of square differences between the calculated response and those desired for all the examples contained in the whole training.

These responses, in this work, are the spectral values in acceleration calculated by the RNA and recorded on the surface of the soil profile characterized by its geotechnical parameters. This profile has a considerable influence on the seismic movement. This influence is taken into account by a classification of sites based on the most significant geotechnical parameters.

CLASSIFICATION OF SITES

In the paraseismic codes, the effect of site is taken into account by introducing certain parameters characterizing the soil. The most used geotechnical parameters are the velocity of shearing waves V_s and the characteristic frequency of site F_0. In the UBC97 building code "Uniform Building Codes, 1997" (Klimis et al., 1998) the average speed of shearing on 30 meters depth V_{s30} is considered. It represents a better degree of confidence with respect to the classification of sites when it concerns a not very deep structure. On the other hand, a deep geological structure, such as the sedimentary basins, can have a strong influence on the effects of site which are not taken into account if a simple classification of site is based only on the upper layers. To overcome these restrictions, a system was developed to characterize a site based on the two parameters: V_{s30} given by equation [1] (Lussou, 2001) and F_0 defined by equation [2] (Das, 1983).

$$V_{s30} = \frac{30}{\sum_{i}^{n} \frac{h_i}{V_{si}}} \qquad [1]$$

$$F_0 = \frac{V_m}{4 \times H} \qquad [2]$$

H: represents the total thickness of the soil profile and V_m the mean of shearing waves speed defined by equation [3] (DTR, 2003):

$$V_m = \frac{\sum_{i}^{n} h_i}{\sum_{i}^{n} \frac{h_i}{V_{si}}} \qquad [3]$$

where, h_i is the thickness of layer i of the soil profile and V_{si} the velocity of shearing waves through layer i.

The sites are classified into four groups: A1 (very crumb soil), B2 (crumb soil), C3 (firm soil) and D4 (rock soil). The letters A, B, C and D represent the classification according to V_{s30}, and the numbers 1,2 3 and 4 describe the classification according to F_0. The coupling between these two parameters (V_{s30}-F_0) gives the classification of sites represented in Table 1.

Table 1: Classification of sites

Type of soil	velocity of shearing waves V_{s30} (m/s)	characteristic frequency F_0 (Hz)
A1: verycrumb	<200	<1.67
B2: crumb	$200 \leq Vs_{30} < 400$	$1.67 \leq F_0 < 3.33$
C3: firm	$400 \leq Vs_{30} < 800$	$3.33 \leq F_0 < 6.67$
D4: rock soil	≥ 800	≥ 6.67

The classification parameters of sites are chosen, the classification is specified. It remains to define the database (DB) used in the training phase. This DB must contain: the thickness, the shearing waves speed in each layer of the profile (to classify the neural networks in accordance to the type of soil) and two types of reference recordings on the surface of the soil profile (input-output couple of the neuronal model).

DESCRIPTION OF THE DATABASE

An authorization was obtained from NIED (National Research Institute for Earth Science and Disaster Prevention), in order to use the soils' profiles and the accelerogrammes for the development of the neuronal system. The official Internet website of the accelerographs network of KIK-NET is: http://www.kik.bosai.go.jp (Bonilla et al., 2003). This network functions on the principle of telemetered stations, and is composed of an accelerograph on the surface and another in-depth (between 80 and 1500 meters).

In the training phase, 10 soil profiles are used and classified according to Table 1. The response spectrum in acceleration; 130 values are recorded on profiles of soils of which the speed of shearing waves for 30 meters depth (V_{s30}) varies between [180 and 1072] m/s and the frequency characteristic F_0 varies between [1.09 and 15.42] Hz, while the total thickness H_S lies between 6 m and 64 m (Table 2).

ARTIFICIAL NEURAL NETWORK ARCHITECTURE

The supervised neural network of Multi-Layer Perceptron type (total connection) is used to generate a response spectrum to the free face from that of reference. The network comprises two inputs (Hurtado et al., 2001) (Figure 2):

Table 2: Profiles of the selected soils and the distribution of the used recordings

Classes of sites	Soil profile code	V_{s30} (m/s)	H_S (m)	F_0 (Hz)	Number of the recordings kept for the training phase
A1	KGWH02	180	54	1.09	21
B2	EHMNH04	254	64	1.41	13
	SMNH07	318	60	1.74	11
	EHMNH07	391	20	3.2	14
C3	SMNH03	445	34	3.35	11
	SMNH02	503	25	4.6	11
	KOCH03	668	32	5.30	15
	SMNH05	711	14	7.5	11
D4	EHMNH03	802	10	11.42	12
	KOCH05	1072	6	15.42	11

- The spectral value in acceleration recorded on a site of reference S_r (damping equal to 5%);
- The value of the proper period (T) corresponding to each point of the response spectrum.

Only the output contains the spectral value in acceleration estimated at the free surface of the ground S_s (damping = 5%).

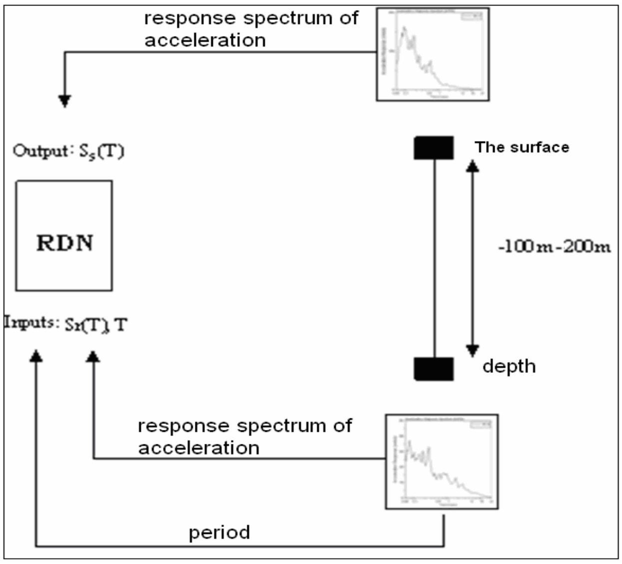


Figure 2: Input and output of the neuronal model

Thus, the neural network gathers a layer of input with two neurons and two hidden layers. The first includes four neurons and the second two and one layer of output with one neuron (Figure 3). The activation function in the output layer is linear f(x) = x and is nonlinear hyperbolic tangent f(x) =Tanh(x) in the two hidden layers. This architecture is adopted after several tests. The latter consists in varying the number of layers and neurons per hidden layer while changing the activation functions of the hidden layers (logistic function, with threshold, Gaussian). Architecture quoted above converges quickly towards the minimal quadratic error (MSE: Mean Square Error) and gives an optimum coefficient of correlation (R) (in the vicinity of 1).

In addition, the free software "ViewWave" version1.3 (Kashima, 2002) conceived especially for the treatment of the accelerogrammes of networks K-NET and KIK-NET, was used in the calculation of the 130 response spectra in acceleration of the training phase.

The principle of response spectrum generation in acceleration to the free face consists in using the spectra recorded in depths (or on a rock) as input of the network and those of surface as output. The retro-propagation method of the error gradient is used for the training. The latter consists in comparing the effective output of the network and the desired output (reality). The training is finished when all the input-output couples are recognized by the network.

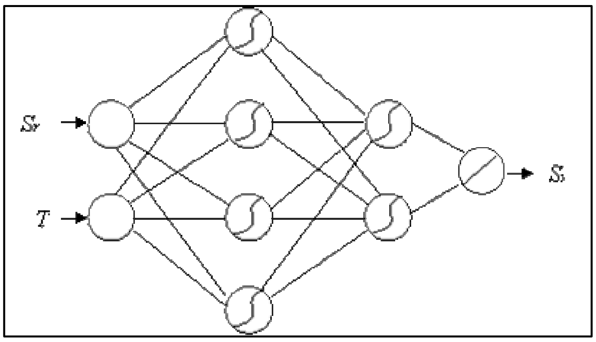
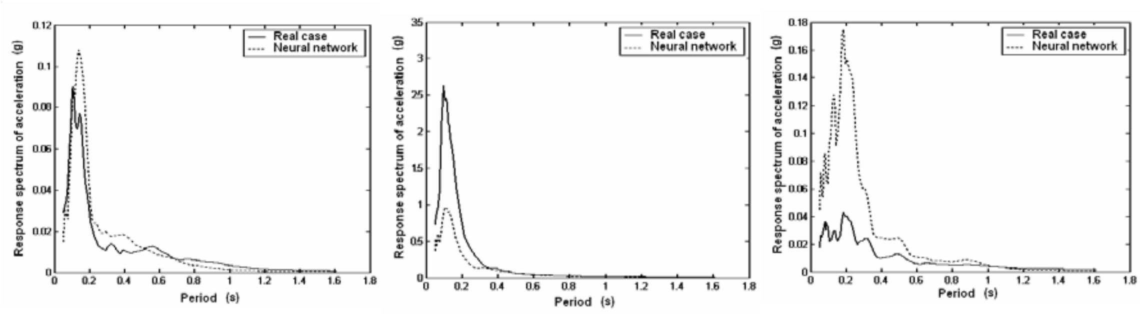
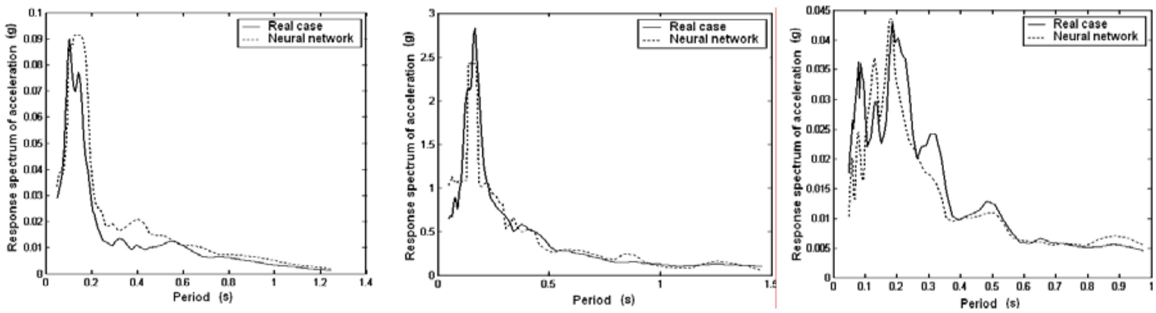


Figure 3: Structure used for the artificial neural network



(a) KGWH02 **(b) SMNH02** **(c) KOCH03**

Figure 4: Response spectra of acceleration estimated by the RNA and calculated starting from real recordings



(a) KGWH02 **(b) SMNH02** **(c) KOCH03**

Figure 5: Response spectra of acceleration estimated by RNA and calculated starting from the real recordings

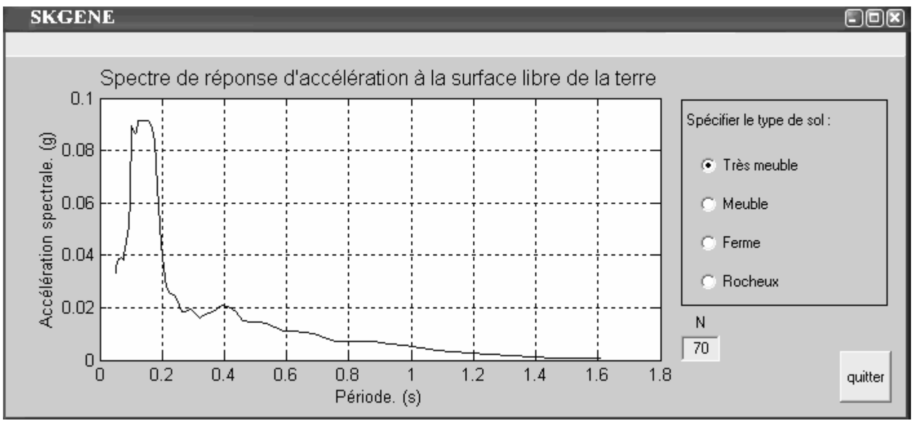


Figure 6: Presentation of SKGENE interface with an execution example

TRAINING PHASE

In the training phase, the adequate choice of the network of neural type, its architecture, its connection and its functions of activation are not the only factors which influence the simulation quality of a response spectrum in free field. The nature of the used data in the development of any model, however, has a very important role in the idealization of the natural behavior.

To test the effect of the local conditions of site on this model, the response spectra of training (input-output) are classified according to the support of recordings (the site).

Thereafter, another classification is added to the first one to evaluate the effect of the maximum input spectral acceleration (recorded in-depth) on the neuronal model.

Classification of the Training According to the Type of Soil

The neuronal system adopted in this part comprises four (4) neuronal networks; each one belongs to a type of soil, namely: A1, B2, C3 and D4. The response spectra in acceleration of each class are used in training of the corresponding network. For example, the neural network of class A1 (very crumb soil) is formed with twenty one (21) response spectra recorded on site KGWH02 which has the following mechanical characteristics: V_{s30} = 180m/s and F_0 = 1.09Hz.

After having conceived the four RNA, a test was carried out with three (3) other response spectra (not used in the training phase), in order to validate the capacity of the RNA. Figure 4 includes the curves S_{as} (spectral acceleration on free surface of the soil) generated by the RNA and those obtained starting from the accelerogrammes.

The generation which seems most satisfactory among the three curves of S_{as} generated by RNA (Figure 6), is that of site KGWH02: the RNA estimates the layout well, except the maximum obtained which is over-estimated in comparison with that of the recording. This maximum is a manifestation of the non-linear nature of the layout. On the other hand, for the other cases the amplitudes of accelerations are different in comparison with the real cases. This difference resides primarily at the level of the peaks. For example, the maximum S_{as} obtained by the RNA (site SMNH02) of the C3 class is about 0.1g but in the real case it is 0.26 g. The increase in the error in the estimation is related to the procedure of network training which is formed with a low degree of non-linearity (passage from low peak to top peak). Consequently, such networks cannot be employed for extrapolation in the event of higher degree of non-linearity. The same phenomenon occurs by using networks formed with spectral recordings which represent peaks raised to estimate spectral recordings with very low peaks as the case of KOCH03. This suggests that several networks must be formed for each range of maximum acceleration (Hurtado et al., 2001), by preserving coupled classification V_{S30}-F_0.

Classification of Training According to Soil Type and the Maximum Acceleration Input

To overcome the problem of non-linearity on the resonance peak levels (passage from low peak to top peak and conversely), a neuronal system was elaborated gathering a hundred and thirty (130) neural networks. Each one is formed with a couple (input/output) of response spectra and is classified according to maximum spectral acceleration of input according to the type of soil: couple V_{s30}-F_0. The same test carried out in the preview section is represented here (Figure 5).

Except the values of the peaks of resonance which are a little different compared to the real peaks, the curves generated by the neuronal system are close to the recordings. All in all, the system adopted in this section practically mitigated the problem of the non-linear behavior at the levels of the peaks for the same sites presented to the neural networks with different recordings.

From these tests, each neural network will be characterized by site conditions (V_{s30} and F_0) and maximum spectral acceleration recorded in-depth (S_r).

GENERAL DESCRIPTION OF SKGENE

So that the neural networks are easily used, an interface under Windows, named “SKGENE” (Figure 6) was created. The introduced data (the spectrum of reference, V_{s30} and F_0) and the results obtained (the spectrum on the surface) are represented on this interface. The latter gathers in its source the 130 networks of artificial neurons, classified according to the type of soil and the maximum spectral acceleration of input. The analysis is carried out in three stages (Derras, 2004):

In the first phase, the user specifies the type of soil (A1, B2, C3, D4), the time increment N (Figure 6) and the file which contains the response spectrum of acceleration of the reference site. This file must be recorded in the same folder as SKGENE and under the name “specter.sce”.

In the second phase, SKGENE calls the neural networks which belong to the same classification site corresponding to the type of soil indicated in phase one, which is made by a logic processing. SKGENE compares thereafter, the maximum value of the spectral acceleration of input S_r (this value is found in the file "specter.sce") and those of the neural networks chosen before. SKGENE selects the neural network characterized by a maximum value near to that of S_r.

In the last phase, SKGENE plots the response spectrum of acceleration estimated by the selected RNA.

VALIDATION OF THE NEURONAL MODEL

The objective is to test the capacity of SKGENE to generate response spectra of acceleration on the ground surface. With this intention, the site of TOTTORI was selected by comparing the response spectra estimated by the computer code SKGENE and those calculated from real accelerogrammes.

TOTTORI 2000 Earthquake

The site of TOTTORI is located in the south west of Japan on the island of Honshu. On 10/6/2000 the region underwent a violent earthquake of a magnitude (JMA: Japan Meteorological Agency) equal to 7.3. The site parameters of 12 profiles of soils are illustrated in Table 3.

Table 3: Codes of stations and sites parameters of 12 profiles

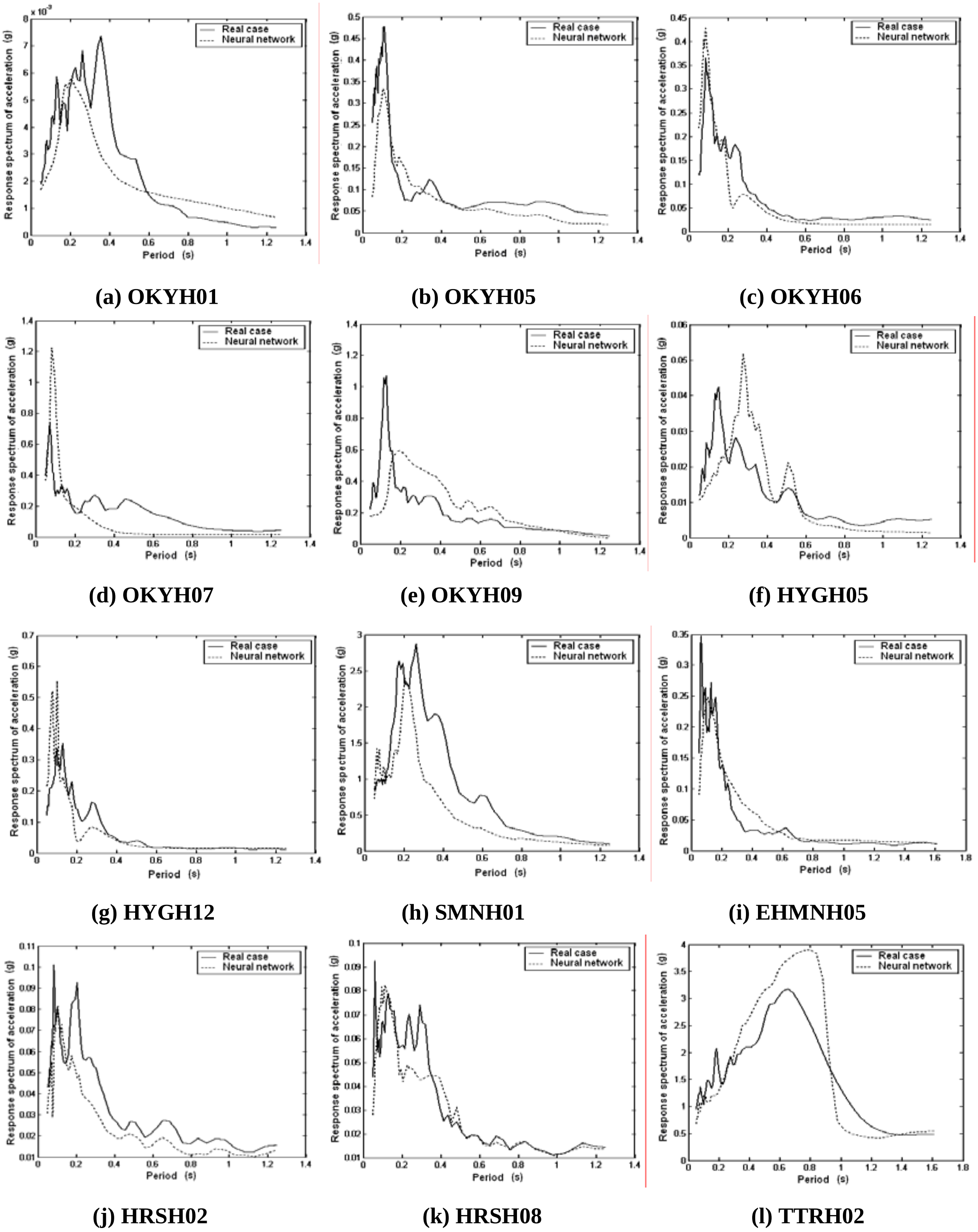
Codes of Stations	V_{s30} (m/s)	H (m)	F_0 (Hz)	Classification of site
OKYH01	236.21	44	1.53	b1
OKYH05	488.15	18	5.89	c3
OKYH06	525.34	24	5.27	c3
OKYH07	929.25	6	10.63	D4
OKYH09	461	21	4.71	c3
SMNH01	464.41	22	4.32	c3
TTRH02	310.21	100	1.38	B2
EHMNH05	362	30	3.02	b2
HRSH08	852	10	14.32	d4
HRSH02	820	12	8.14	d4
HYGH12	615	13	8.4	D4
HYGH05	527.86	13.5	5.45	C3

The recorded response spectra in-depth are introduced into SKGENE. They are represented with those recorded on free face in Figure 7.

The comparison between curves obtained by SKGENE and those starting from the recordings (Figure 7) reveals that, generally, the generated spectral accelerations are close to those calculated starting from the accelerogrammes. In a particular way, the maximum spectral values calculated by the neuronal model are different in terms of frequency compared to those from the real case in curves (d) and (g).

Acceleration is over-estimated for the low periods and is underestimated for the periods which exceed 0.2 s. On the other hand, in the curve (e) SKGENE underestimated the amplitudes which are lower than 0.2s and over-estimated those which belong to mid and high periods. For curve (c), the spectral values are the same as ones and the frequency converges towards that obtained values in the real case. The curves (a), (b), (f), (h), (j) and (k) simulated by the neuronal model are very close to those recorded. The small differences lie primarily at the levels of the maximum amplitudes as well as in the frequential contents. These small differences are primarily due to three factors:

The first is related to the classification of site, profiles OKYH01 and HYGH12 (class B1 and C4, respectively) are incompatible with the classification used in the development of the model. Site OKYH01 belongs to a crumb soil if one considers V_{s30} and very crumb if F_0 is the only parameter of classification. The second factor is the medium behavior with respect to the seismic stress. For the strong movements such as the earthquake of Tottori M_{jma} = 7.3, the behavior of the soil becomes nonlinear. In this context, Figure 8 represents two spectral accelerations at the surface and in-depth (-100 m) of station TTRH02, in which the nonlinear behavior of the soil leads the period to undergo the prevalent period (period corresponds to the resonance peak) of 0.07s to 0.65s. This variation is evaluated by this model with a small overestimation of the maximum amplitude. On the other hand, in curve (i), the neuronal model gives a prevalent period (2.8s) different from that recorded (1.4 s) with an amplification appreciably higher than that from the real case. The same explanation remains valid for curves (d) and (e). The third factor depends on the number of response spectra of the training phase used for each class. Thus, the quantity of spectral data plays a big role during the generation of a spectrum of answer to the free face. A correct estimation of a spectrum is due primarily to the resemblance between the generated values and those of training.



(a) OKYH01 (b) OKYH05 (c) OKYH06

(d) OKYH07 (e) OKYH09 (f) HYGH05

(g) HYGH12 (h) SMNH01 (i) EHMNH05

(j) HRSH02 (k) HRSH08 (l) TTRH02

Figure 7.Response spectra of acceleration estimated by SKGENE and calculated starting from the real recordings

CONCLUSION

The complexity of the medium crossed by the seismic wave and the scarcity of the accelerogrammes data recorded on the same medium, motivate the engineer to seek for a less expensive numerical model. The method of multi-layer neurons networks of the Perceptron type proved to be an appropriate solution for the problems quoted before. This one is used for the generation of response spectra in acceleration to the free surface of a soil profile.

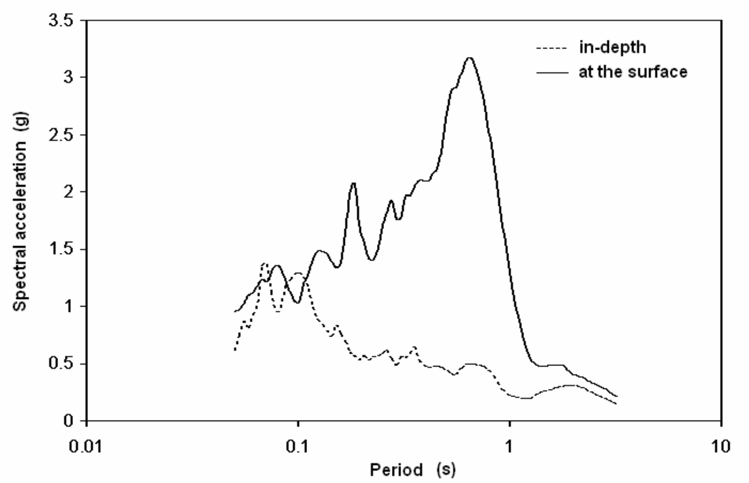


Figure 8: Response spectra of in-depth acceleration and on the surface, recorded at the level of station TTRH02

If the medium excited by the seismic stress and the maximum spectral acceleration recorded on site of reference are taken into account, this method can give indications on the spectral curves in acceleration generated to the free face. These indications are translated by the spectral paces obtained by SKGENE, which are close to those calculated by the accelerogrammes. This behavior close to that of the real case is primarily due to the existing resemblance between the generated values and those of the training. The widening of the database in term of spectral accelerations and of the soil profiles in the training phase is thus desirable to improve the obtained results.

REFERENCES

Bekkouche, A., Derras, B. and Zendagui, D. 2005. Quantification et estimation du risque lié à l'effet de site par la méthode neuronale. *23ème rencontres universitaires de génie civil AUGC*, mai 2005, Grenoble, France.

Benouar, D., Gilbert, L.M. and Yamazaki, F. 1998. Mapping seismic hazard in the Maghreb countries: Algeria, Morocco, Tunisia, *11th European Conference on Earthquake Engineering*, Balkema, Rotterdam, ISBN 90 5410 982 3.

Bonilla, L.F., Cotton, F. and Archuleta, R.J. 2003. Quelques renseignements sur les effets de site non-linéaires en utilisant des données de forage : la base de mouvements forts Kik-net au Japon. 6ème colloque national AFPS, juillet 2003, Paris, France.

Chu-Chieh, J.Li. and Jamshid, G. 2001. Generating multiple spectrum compatible accelerograms using stochastic neural networks. *Earthquake Engng. Struct. Dyn.,* 30: 1021–1042.

Das, M. 1983. Principles of soil dynamics, PWS-KENT. Publishing Company Boston, USA.

Derras, B. 2004. Estimation du risque lié à l'effet de site et génération d'un spectre de réponse à la surface libre, Mémoire de Magister, Université de Tlemcen.

DTR B C 2 48. 2003. Règles parasismiques algériennes- R.P.A.99 version 2003, Document technique réglementaire, centre national de recherche appliquée en génie parasismique, Ministère de l'habitat, Algérie.

Ghaboussi, J. and Lin, C.J. 1998. New method of generating spectrum compatible accelerograms using neural networks, *Earthquake Engineering and Structural Dynamics*, 27: 377-396.

Goh, A.T.C. 1994. Seismic liquefaction potential assessed by neural networks, *ASCE Journal of Geotechnical Engineering*, 120: 1467-1480.

Guillaume, Pousse. 2005. Analyse des données accélérometriques de K-NET et KIK-NET: implications pour la prédiction du mouvement sismique -accélérogrammes et spectres de réponse et la prise en compte des effets de site nonlinéaire. Thèse de Doctorat, octobre 2005, IRSN-2006-65.

Hervé, A. 1994. Les réseaux de neurones, Science et technologie de la connaissance, Presses universitaire de Grenoble, France.

Hurtado, J.E., Londono, J.M. and Meza, M.A. 2001. On the applicability of neural networks for soil dynamic amplification analysis, *Soil Dynamics and Earthquake Engineering*, 21: 579-591.

Juan, R.R. and Julián, D. 2006. Artificial neural networks in real-life application. IDEA GROUP PUBLISHING IGP.

Kashima, T. 2002. ViewWave Help, IISEE, BRI.

Klimis, N.S., Margaris, B.N. and Koliopoulos, P.K. 1998. Response spectra estimation according to the EC8 and NEHRP soil classification provisions: a comparison study based on Hellenic data, *11th European Conference on Earthquake Engineering*, Balkema, Rotterdam, ISBN 90 5410 982 3.

Laouami, N., Slimani, A., Bouhadad, Y., Nour, A. and Larbes, S. 2003. Caractérisation du séisme de boumerdès -analyse sismique des enregistrements obtenus lors du choc principal du 21 mais 2003, Colloque International, Risque, vulnérabilité et fiabilité dans la construction, Alger, Algérie, 686-699.

Lussou, P. 2001. Calcul du mouvement sismique associé à un séisme de référence pour un site donné avec prise en compte de l'effet de site. Méthode empirique linéaire et modélisation de l'effet de site non-linéaire, Thèse de doctorat, Université de Grenoble.

Paolucci, R., Colli, P. and Giacinto, G. 2000. Assessment of seismic site effect in 2-D alluvial valleys using neural networks, *Eartquake Spectra*, 16 (3): 661-680.

Seung, C.L. and Sang, W.H. 2002. Neural-network-based models for generating artificial earthquakes and response spectra. *Computers and Structures*, 80: 1627-1638.

Shin, A., Takashi, K. and Hiroyuki, F. 2004. Strong-motion seismograph network operated by nied: k-net and kik-net, *Journal of Japan Association for Earthquake Engineering*, 4 (3).

Tienfuan, K. and Ting, S.B. 2005. Neural network estimation of ground peak acceleration at stations along Taiwan high-speed rail system. *Engineering Applications of Artificial Intelligence,* 18: 857-866.

Vincenzo, C., Iunio, I., Aldo, Z. and Gaetano, M. 2007. Prediction of response spectra via real-time earthquake measurements. *Soil Dynamics and Earthquake Engineering*, Article in press.

Yu, H.H. and Jenq, N.H. 2002. Handbook of neural network signal processing. CRC Press, ISBN 0-8493-2359-2.