NEW METHOD FOR GENERATION OF ARTIFICIAL EARTHQUAKE RECORD

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ABSTRACT :

In this paper, the use of wavelet analysis and artificial neural networks for generating artificial earthquake accelerograms from the target spectra is suggested as a new method. This procedure uses the learning capabilities of neural network to expand the knowledge of the inverse recording from response spectra to earthquake accelerogram. In the first step, wavelet analysis is used to decompose earthquake accelerograms to several levels in which each level covers a special range of frequencies, and then for every level a neural network is trained to learn to relate the response spectra to wavelet coefficients. Finally, the generated accelerogram using inverse discrete wavelet transform is obtained. An example is presented to demonstrate the effectiveness of the proposed method.

KEYWORDS: Artificial accelerogram, target spectra, wavelet analysis, neural network

1. INTRODUCTION

One of the most important factors in designing structures resistant to earthquakes is dynamic analysis on the basis of response spectra or time-history method. Although the response spectra method is quite simple for analysis and design of linear buildings and other structures, it has a weakness on providing time data about the response of the structure when often this data is essential to achieve an appropriate design. Thus, regarding the daily growing usage of dynamic time-history analysis for calculating the structural response caused by lack of proper and sufficient records, nowadays, generation of artificial accelograms is indispensable.
So, different random stable and unstable models for inspection of seismic ground motions and generation of artificial records have been widely used in books and references. Regarding that in structure and earthquake engineering phenomena such as earthquake, explosion, impact and wind are considered as unexpected events and their behaviors do not follow any regulations, many efforts have been made to model and regulate the phenomena in order to recognize and evaluate and also predict their behaviors. Generating the artificial earthquake records is done in many ways but generally they are divided in two groups, geophysical and random methods [1]. Since the geophysical models are not developed yet, random models are more common and many diverse patterns are presented on this basis. By reason of complicated mechanism making seismic waves and the way of distribution before they reach the specified station, a time dependant examination could be helpful in generating a proper artificial accelogram.
The advance calculating ability of the Fourier analysis makes it the most versatile tool which could be used in diverse applied fields. Fourier transform shows the signal in frequency domain and gives some information about which frequencies are appeared in signals but it does not discuss about time content of these frequencies. In fact, by the aid of Fourier analysis, the physical explanation will be simple. On the other hand, Fourier analysis is not suitable for all models and patterns or signals in view of the fact that many natural phenomena are almost non-linear.
For the reasons mentioned above, other methods that explain the combination of time-frequency are used and many attempts have been devoted in order to develop the time-frequency methods which allow momentary illustration of behavior of one signal.
After the stable approaches, new methods on the basis of unstable time-dependant were presented for generation of artificial earthquake accelograms such that Generalized Non-stationary Kanai-Tajimi model [2]. In Kanai-Tajimi non-stationary model, non-stationary process is taken by the aid of moving time-window technique with the proper, changing and approximate stationary lengths [3].
Generalized Non-stationary Kanai-Tajimi model is used to explain and simulate time-history ground motions in both non-stationary time and frequency domains. In this model, moving time-windows are utilized to calculate the parameters of time variable of the model by the use of real earthquake records [4].
One of the well known models presented for generation of required records is auto regressive moving average model (ARMA) which is a general linear model for analysis of discrete time series [5].
Yeh and Wen [6] made a random time dependant model for generating ground motions by the aid of three functions of intensity, frequency module and the density of power spectra. On the other side, according to great application of artificial neural networks in structural engineering and particularly in analysis of structural dynamic problems, this method has been widely used. One of the researches about the application of artificial neural networks for generating artificial accelograms compatible with response spectra is one which is done by Ghabousi and Lin [7].
Considering the future design for building structures, especially those that encounter enormous, spread and dangerous loads, it is essential to review the frequency content and measure it in time changing (time periods). Besides, time analysis and frequency analysis are not able to explain solely the non-stationary spectra of dynamic loads correctly. In previous years, great efforts have been made using the Wavelet analysis model in time-frequency models.
By the appearance of wavelet conversions as a powerful tool in time-frequency analysis, an opportunity is provided that the inspection in non-stationary frequency field is performed much more accurately. Wavelet analysis like the Fourier method is mathematically based and is a useful tool for the time-history analysis [8]. This theory enables us to recognize the frequency content in each time step (interval) [9].
Research shows that although the definite pattern in recognition of earthquake records (even in specific zones)

would not be achievable; response spectra related to them generally have many resemblances that in some cases could lead into quite definite patterns for the spectra related to a specific area. Thus, scholars, by smoothing such spectra, could reach a plane and smooth spectra called design spectra. Studies have been followed up to a status that could demonstrate the design spectra for every zone considering the geophysical and geotechnical characteristics. Such spectra are applied generally in controlling the authenticity of artificially generated earthquakes and the goal is that the response spectra of simulated records have an acceptable proximity with the presented design spectra. Such design spectra used for control are called target spectra.
It should be mentioned that superposing of response spectra with the goal spectra is not evidence of correct because it could be possible that different diagrams exist identical to response spectra. If the calculation of response spectra related to a record is considered as a straight problem, finding the accelogram regarding the related spectra would be a reverse of the indicated problem. A response spectrum could not reach a specific record because some characteristics would be omitted in calculation of response spectra. Hence, accelograms with different specifications may have the same response spectra.
In this paper firstly, some applied contexts are explained and secondly, a method for generation of artificial accelogram compatible with response spectra will be presented. In this method, artificial neural networks, wavelet analysis and LPC coefficients are utilized. Finally, by controlling the results, we evaluate the accuracy of the method.

2. WAVELET ANALYSIS

Wavelet conversion is a kind of conversion that extracts frequency specification of a signal from a short period of time and explains that, by passing time, how the frequency parts change. In this conversion, a series of basic vectors are made that the display of a signal on the basis of the vectors is equivalent to frequency element of the signal. Since for each frequency resolution these basic vectors are changed, frequency elements in different resolutions are obtained. Wavelet theory gives us an opportunity that in non-stationary processes, we get information about the frequency elements every second. Additionally, wavelet analysis, in comparison to Fourier analysis, presents a local behavior, contrary to Fourier analysis which shows a general (global) behavior. Wavelets are developed independently in many majors like mathematics; quantum physics, electronic engineering and they become powerful tools which are utilized in those majors [3].
When a discrete wavelet conversion is used, two filters are applied to the signal. One filter conquers the kind of signal approximation and the other masters the deviations or signal approximation details. The former refers to scale filter or scale function and the latter refers to wavelet or the wavelet filter. Figure 1 shows the process.
In fact, applying the scale function or wavelet is the same as a moving window in the extension of the signal. Capturing the local behavior is defined by the scale function and wavelet in time. Every window is determined by displacement of the scale function and wavelet to the right side by multiplying the main signal to the displaced scale function and wavelet.
This was the first step. The above mentioned process is repeated and is done the repetition in each time position so that the signal's approximate series are obtained. Then in each level a new separation between details and approximate signals from signal's approximation is made. The method of performance has been discussed in Figure 2, which is called wavelet's resolution tree [3].

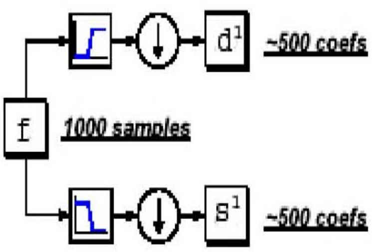

Figure 1 Wavelet filter [10]

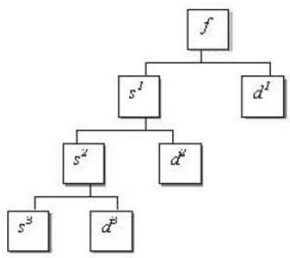

Figure 2 Wavelet analysis tree [3]

In Wavelet analysis a details part in level J is defined as bellow:

$$D_j(t) = \sum_{k \in Z} cD_{j,k}\, \psi_{j,k}(t) \tag{2.1}$$

In which Z is a set of positive integers, and $cD_{j,k}$ are Wavelet's factors in level J which are defined in the order below:

$$cD_j(k) = \int_{-\infty}^{\infty} f(t)\psi_{j,k}(t)dt. \tag{2.2}$$

An approximate part in level J is defined in this manner:

$$A_j(t) = \sum_{k=-\infty}^{\infty} cA_j(k)\phi_{j,k}(t). \tag{2.3}$$

In which $cA_{j,}$k are scale's factors in level J which are defined in the order below:

$$cA_j(k) = \int_{-\infty}^{\infty} f(t)\phi_{j,k}(t)dt. \tag{2.4}$$

At the end f (t) signal is shown in this manner:

$$f(t) = A_J + \sum_{j \le J} D_j \tag{2.5}$$

3. ARTIFICIAL NEURAL NETWORK

Artificial neural networks are one of the new subjects in computer science that many scholars have become interested in devoting their time and incurring considerable expense on its improvement. Originally, this idea was inspired by the neural network of the human body and comparisons were made between computers and human beings. Now, many scientific and applied activities of artificial neural networks in technical-engineering affairs like control systems, signal processing, identifying the patterns and modeling have been developed.
One ordinary artificial neural network is consisted of several layers, and each layer includes some little elements called neurons, cells, units or nodes. The structure of a network is composed of different layers accompanied by some related neurons. The first layer of every network is named input layer and the last layer is called output layer, whist the middle layers are termed hidden layers. Usually, neurons of each layer connect to all the adjacent layers by a directed connection. In Figure 3 a sample of this structure is illustrated. The data is displaced between the neurons through the connections. Every connection has a particular weight which is multiplied by the data in displacement from one neuron to another. Every neuron, for calculating its output, imposes an activation function (usually a non-linear function) on the inputs (that are sum of weighted data). In addition to input nodes, one extra node called bias with the unit value is also connected to the next layer, without any effects from the neuron outputs of previous layer. Existence of this neuron and the weight specified to it has a constant value for input data and it causes a shift in circumstance of input curve. This value could be equivalent to a constant number in multi-sentence phrases. Therefore, if we want to omit it, the activation function should get a threshold value and opposite to zero that can be shift in entrance to each neuron [11&12].

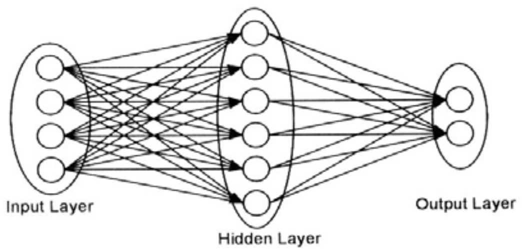

Figure 3 Sample of one ordinary artificial neural network

3.1. Multi-layer Feed-forward neural network (MLFF)

Feed forward network is a multi layer perceptron that includes an input layer from the source nodes, one or more hidden layers with calculating neurons and one output layer. The source nodes are for entering the input data and the hidden layers perform like specification detectors. As mentioned, these neurons are also known as hidden neurons because there is no access to them from both the input and output. The outputs of the output layer are as the output of the neural network [11].
The hidden layer neurons have the activation function. One artificial neuron model is shown in Figure 4. This model is composed of a linear combinator and one non-linear function. The linear combinator includes synaptic weights. Input of the linear combinator is the output of the real previous neurons and its output is sum of the weights multiplied by inputs. Then, this sum is being passed through a non-linear section and conform the external or output of the real neuron [3].

$$y = \Phi\left(\sum_{i=1}^{N} w_i x_i + b_1\right) \tag{3.1}$$

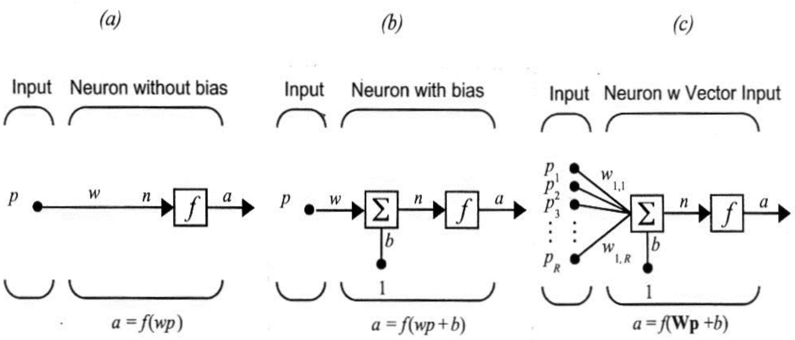

Figure 4 Model of an artificial neuron [10]

In this way two specifications could be explained:

- The above function is a pioneer function where the input signal generates a response in the forward path at the exit or in other words, there is not any feedback.
- The network has complete connections; it means that every node in each layer connects to next layer nodes.

For designing the multi layer pioneer network, three points should be answered:

- defining the hidden layers
- defining the number of neurons in every hidden layer
- defining the weights between connections

The first and the second instances are an explanation of the complexity of the network. Defining the hidden layers and neurons of each hidden layer is one of the important cases in neural network and as yet, has not found a systematic way to define them. [13]

4. LPC ANALYSIS

Linear predictor coefficients model is a proper tool for signal analysis. This model generates the coefficients by the aid of a system called IIR and can be better displayed with fewer points in regard to the main signal. (Figure 5) Generally, a problem in LPC can be explained as finding a_k coefficients in the following model that the average aggregate of square errors of signal sample S becomes minimum. [14]

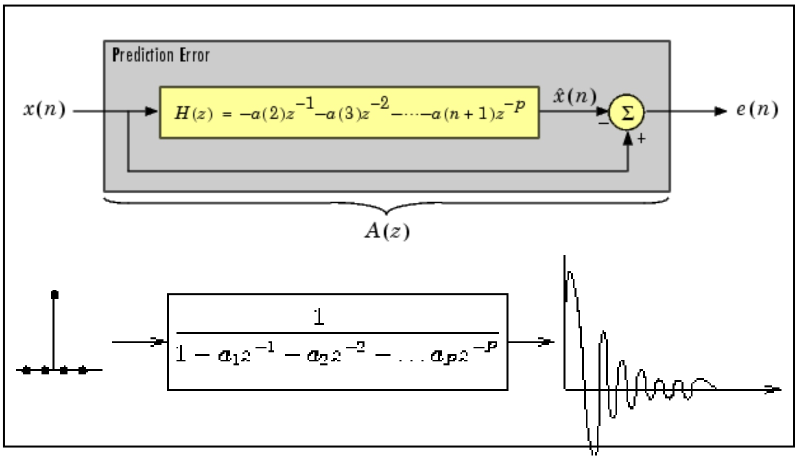

Figure 5 Linear predictor coefficients model [10]

In this model, finding the coefficients of a linear predictor is done by the usage of real X time series current values according to the previous cases.

$$x(n)= -a(2)x(n-1)-a(3)x(n-2)-\ldots-a(p+1)x(n-p) \qquad (4.1)$$

5. PROPOSED METHOD

In this section a new method on the generation of artificial acceleration records will be presented. In this method the compatible records with response spectra are generated using neural networks, wavelets and LPC's compressing method which the base of each were discussed in the previous sections.
What is presented in the introduction can be applied as a basis for a new method of generating artificial records compatible with target spectra for a particular area. As it is known goal of generating such records is to use them for dynamic analysis of structures, in situations such as record selection which is counted as insignificant earthquake won't present a suitable analyze. Because in that way the structure won't have a considerable reaction to it. Most of the registered records in Iran have such features. The basic data of Iran's acceleration recording Network has been presented in reference number [15]. Most of these records have lower volume and low maximum acceleration so they can't be counted as a good educational pattern. Among all these records less than 20 records have acceptable features, and the other point is that these series of records belong to different areas with different features therefore educating a network with such features seems to be undoubtedly complex. At the end with a little connivance 40 acceleration records can be selected for the educating and testing of the network.
As mentioned in the previous sections, Wavelets have the ability to decompose any time series to a number of separated, commonly vertical levels. Actually this is the basis of the method which is discussed in this paper. In fact here the combination of neural networks, Wavelets and LPC compressing has been used in order to reach an artificial acceleration records with a response spectra similar to Target spectra. In this method input response spectra of earthquake signals and output is earthquake signals which Wavelet analysis and LPC have been applied to.
In network education, if it can be equalized the mentioned parameters in all records, we will in fact have made it more facile. One of the above mentioned cases is earthquake duration time which with the following method it is clear that the number of different record points have to be somehow equalized. Since there is a linear relation between acceleration records and response spectra, and also presented target spectra for network use generally are like normalized spectra for a particular maximum acceleration, this maximum acceleration has to be applied more considerably to the picture. For this purpose all the mentioned records have been scaled to a particular maximum acceleration. This way all records have been equalized in duration length and the Earthquakes maximum acceleration. Also by putting the impressive acceleration of all records in one particular point, as in Figure 6, the information of signals has been simulated to each other in order to teach the network.

If we put a decision on selecting N= 2^{12} points, a one good way is to transfer the mentioned records on the time line so that all of their maximum acceleration come up in one particular point. It is one of the methods which helps the improvement of output, in order to facilitate networks learning. So the achieved records of this method are the best for using in network [7].

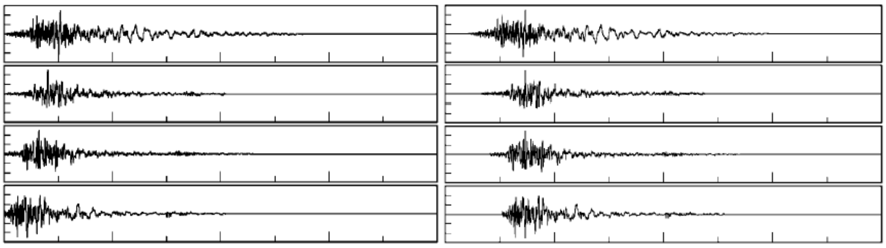

Figure 6 Signal normalization (Left: Before Normalization, Right: After Normalization)

After normalization, the wavelet analysis applies for each signal. For each Wavelet's decompress level one MLFF neural network is designed, here according to applied frequency bounds, records are decomposed to 8 levels. Other levels are not usable for us because of a very high frequency. In this manner a velocity response spectra is supposed as a network's input. Here we will have 9 networks for generating the signal's wavelet factors and the final acceleration records will come out from the sum of these networks's output is the input for all networks. It is clear that according to the equalization of all record's PGA resulted spectra are all related to 1 g maximum acceleration. The response spectra of each record, having been calculated with Seismosignal software [16] with 0.05% mortality rate in 100 frequency point. The networks features have been presented in Table 1.

Table 5.1 Networks features

Net. Number	Number 1	Number 2	Number 3	Number 4	Number 5	Number 6	Number 7	Number 8	Number 9
Net. Input	Response Spectra (100 node)								
Net. Output	D1	D2	D3	D4	D5	D6	D7	D8	A8
Output number	1033	526	272	145	82	50	34	34	34

In the network education with the above mentioned situations, the problem of numerous numbers of input and output nodes exists. For resolving this problem in networks, the output signals are approximated using LPC analysis and consider output nodes as LPC factors of each level. Now according to the above mentioned network the education of network with available data can be done, it is necessary to mention that in each network education a series of data is selected as educational ones, and a number of them are selected as testing ones. So here 34 records are used for network education and 6 records for the network test. The testing records are selected randomly.
In order to achieve calculation with the use of LPC factors the Wavelet's reverse operation has been used. A sample test results with a generated response a generated artificial signal, two signal spectra of them are shown in figures 7 and 8.

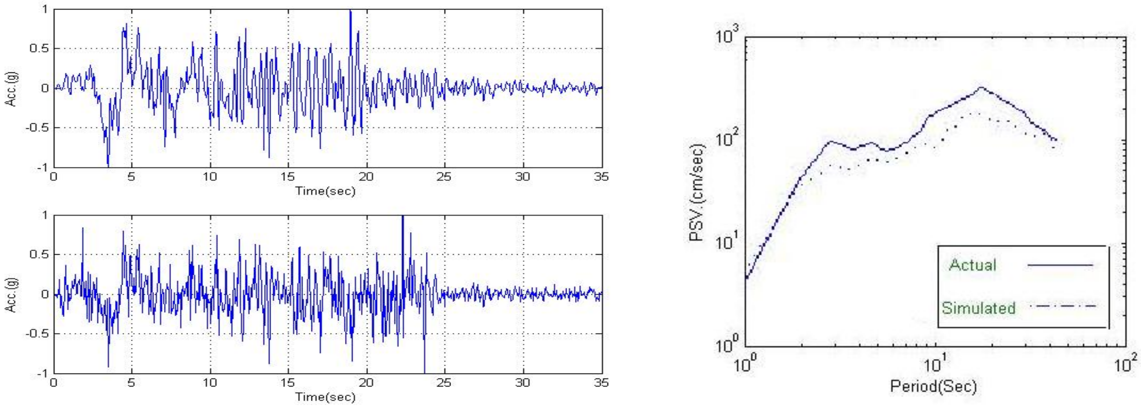

Figure 7 Original accelerogram (Left-Top), Artificial (Left-Button) of BAM Signal & Related Response Spectra (Right)

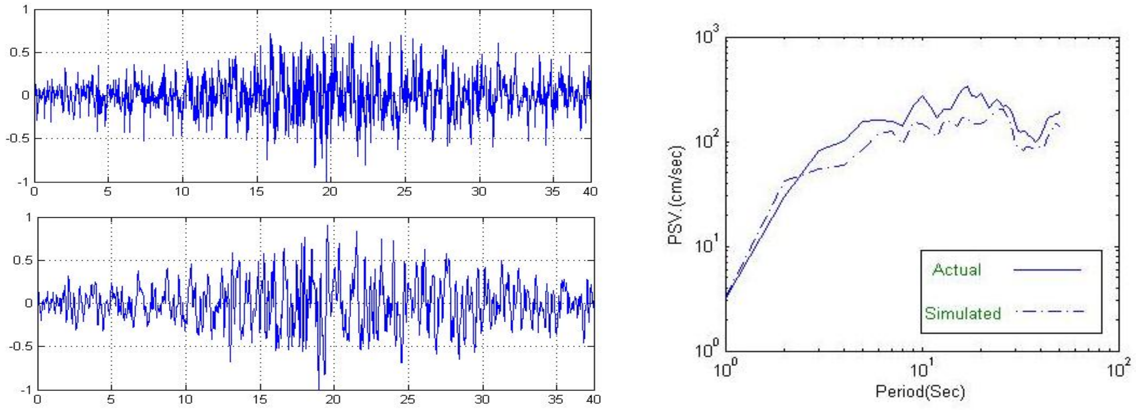

Figure 7 Original accelerogram (Left-Top), Artificial (Left-Button) of MANJIL Signal & Related Response Spectra (Right)

6. CONCLUSION

In this paper a method for generation and simulation of the acceleration records has been presented. By comparing the results it can be concluded that generated acceleration records contain the most frequency content of the actual acceleration records, and the response spectra of artificial acceleration records properly adjusted to the response spectra of actual acceleration records.
By comparing the figure of artificial and actual acceleration records we can conclude that the mentioned pattern somehow, has the ability of simulating a figure of records. Also by comparing the response spectra we notice that the average of generated record's response spectra is properly adjust to the average of generated record's response spectra. Therefore it can be considered that a presented pattern can simulate the earthquake from the domain and frequency content points of view.
In the mentioned method, the records are decomposed using Wavelet analysis and LPC, and then the relation between response spectra, LPC factors and Wavelet is approximated using MLFF neural networks, at the end we will gain to consider acceleration records using reverse Wavelet's transformation. One of the important features of this method is the use of LPC compressing method which is used on coding the acoustic signals.
From advantages of the above mentioned method it can be referred to:

- The non random nature of outputs, so that the acceleration records can be supposed as the results of input patterns.
- The use of Wavelet analysis on extraction and recognition of record's frequency's features.
- The reduction of neural network's size using LPC analysis.

A good flexibility, which means that with a few numbers of patterns, we can reach a good response for a particular input.

REFERENCES

1. MacCann, W.M. and Shah, H.C. (1979), "Determining strong-motion duration of earthquake", *Bulletin of the Seismological Society of America*, Vol. 69, pp. 1253-1265.
2. Ahmadi, G. and Fan, F.G. (1990), "Nonstationary Kanai-Tajimi models for E1 Centro 1940 and Mexico City 1985 earthquake ", *Probabilistic Engineering Mechanics*, Vol. 5, pp. 171-181.
3. Baheri, A. (2005), "*Generation of Artificial Acclerogram by Using Kanaei-Tajimi Model and Wavelet*", M.Sc. Thesis, College of Civil Engineering, Iran University of Science & Technology, Tehran, Iran.
4. Ghodrati Amiri, G., Raeisi Dehkordi, M. and Bagheri, A. (2005), "Generation of artificial earthquake records with a nonstationary Kanai-Tajimi model and wavelet transform", *Proceedings of the International Symposium on Innovation & Sustainability of Structures in Civil Enginieering Including Seismic Engineering*(ISISS'2005), Nanjing, China, November 20-22.
5. Olafsson, S. and Ragnar, S. (1995), "Application of ARMA models to estimate earthquake ground motion and

structural response", *Earthquake Engineering & Structural Dynamics*, Vol. 24, pp. 951-956.

6. Yeh, C.H. and Wen, Y.K. (1990), "Modeling of nonstationary ground motion and analysis of inelastic structural response", *Structural Safety*, Vol. 8, pp. 281–98.
7. Ghaboussi, J. and Lin, C.J. (1998), "New method of generation spectra compatible accelerograms using neural network", *Earthquake Engineering & Structural Dynamics*, Vol. 27, pp. 377-396.
8. Newland, D.E. (1994), "*Random Vibration, Spectral and Wavelet Analysis*" 3rd Edition, Longman Singapore, Publishers.
9. Ghodrati Amiri, G., Ashtari, P. and Rahami, H. (2006), "New development of artificial record generation by wavelet theory" *Structural Engineering and Mechanics*, Vol. 22, pp. 185-195.
10. MATLAB Reference Guide, The Math Works, Inc., 2007.
11. Menhaj, M. (1998), "*Calculation Intelligence: Neural Network*", Amirkabir University, Iran.
12. Kaveh, A., Iranmanesh, A. (1999), "Artificial neural network in structural optimization", Building & Housing Research Center, Publicatio No. 310, Tehran, Iran.
13. Rahami, H. (2000), "Generation of Artificial Accelerator by Using Artificial Neural Networks", M.Sc. Thesis, Department of Civil Engineering, Faculity of Engineering, Tehran University, Iran.
14. Proakis, J.G. and Manolakis, D.G. (1996), "*Digital Signal Processing: Principles, Algorithms, and Applications*", Upper Saddle River, NJ: Prentice-Hall.
15. Ramazi, H. (1997), "*Database of Accelerator in Accelerogram Network of Country*", Building & Housing Research Center, Publicatio No. 256, Tehran, Iran.
16. Seismosignal Software. Autumn, Seismosoft Inc., 2002.