SEISMOLOGICAL PARAMETERS INFLUENCE ON PGA PREDICTION BY A NEURAL NETWORK APPROACH

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ABSTRACT

The Peak Ground Acceleration (PGA) is an important parameter widely used for assessing the earthquake effects at a given site and also for the development of design response spectra for seismic calculation use. The aim of this paper is to predict the PGA and investigate the effect of seismological parameters using feed forward artificial neural network. For this purpose, the KiK-net database is used to extract a selection of 1104 records, and a multi-layer perceptron architecture with the error back-propagation learning algorithm has been adopted to develop a model correlating the PGA to the following independent variables: earthquake magnitude $M_{\text{ijm}}$, the focal depth $d$, source-to-site distance $R_{\text{epi}}$, the shear-wave velocity down to 30 m ($V_{S30}$) and resonant frequency ($f_{\text{800}}$). An analysis of the effect of directionality on the PGA was performed, and it was found that a principal direction with respect to the E-N direction can be obtained for which corresponds an increase of the PGA that may reach up to 35%. Therefore, a radial angle parameter has been included in the input of the ANN model. Finally, a sensitivity analysis was carried out for each input parameter in order to evaluate the weight of their influence on the PGA. The results indicated that the predicted values of the PGA by the neural network are in good agreement with the corresponding target values. The performance analysis of the input parameters shows that the epicenter distance and the newly introduced radial angle are first order parameters influencing the PGA compared to the depth and shear-wave velocity which have a less significant impact.

Keywords: Seismological parameters, earthquake ground motion, artificial neural networks, KiK-net network, Peak Ground Acceleration.

1. INTRODUCTION

The characterization of ground motion is a fundamental step in seismic analyses of structures subjected to earthquake ground motion. Effects of seismological parameters on the seismic action are not explicitly incorporated in current design practice. In recent years, several authors have proposed methods to estimate realistic seismic movements on the basis of a stochastic parameterization in the temporal domain. The ground motion characteristics have an important influence on the seismic behavior of buildings, including ground motion intensity (Vamvatsikos and Cornell 2002) (Tothong and Luco 2007), duration (Bommer and Martinez-Pereira 1999) (Raghunandan et Liel 2013), frequency content (Kumar, et al. 2011).

Peak ground acceleration (PGA) is one of the key elements to assess the importance of seismic action and still often used as a parameter to describe strong ground motion and to scale earthquake design spectra, the question that then arises is how to estimate the PGA at a site where no recording station is installed. The ground motion features are influenced by a number of factors which can be classified into three groups: 1) Source characteristics, 2) Path characteristics 3) Site characteristics.

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The prediction of the PGA in terms of seismological parameters has been widely investigated in literature and various models have been proposed to estimate PGA, a summary statement has been carried out (John 2011) for all empirical ground motion prediction equations (GMPEs) proposed for PGA since 1964. Researchers have chosen their techniques based on the available data from past earthquake, which varies greatly with geographical region. However there is still a need to include more independent parameters into ground motion estimation equation (John 2003).

In this paper, the artificial neural network (ANN) technique is used as an alternative to regression methods. The ANN with Back-Propagation (BP) learning algorithm is strongly recommended for highly nonlinear modeling problems. It has been used to develop methods to generate spectrum compatible accelerograms (Jamshid and Chu-Chieh 1998), as well as the prediction of ground time history responses (Derbal et al. 2017).

Concerning the prediction of the PGA by ANN method few recent studies were performed Gunaydın and Ayten 2008 have used three different artificial neural network to predict PGA in the northwest region of Turkey, (Kerh and Ting 2005) have used ANN method to estimate PGA using a limited network for ten station deployed along the train track in Taiwan. The feed forward ANN has been used by (Derras and Bekkouche 2011) to estimate PGA using KiK-net data.

The objective of this work is to predict the PGA of the strong ground motions with an additional input parameter and analyze the influence of seismological parameters on the PGA using feed forward artificial neural network (ANN) with a conjugate gradient back-propagation rule for the training. The inputs are the magnitude, the focal depth, the epicentral distance, shear-wave velocity and the radial angle epicenter-station while the target output is the PGA. Then, a sensitivity analysis is carried out in an attempt to capture the influence of the seismological parameters on the PGA. Moreover in the existing models the peak ground acceleration due to different orientations was not explicitly incorporated and it was based on geometric mean or the maximum of the two orthogonal components. The models developed in this paper take into account both components by introducing a new parameter as an input called the radial angle for each component.

2. GROUND MOTION DATABASE

The strong motion database developed in this study includes approximately 1104 records from 10 events ranging between Mjma (Japan Meterological Agency Magnitude) = 4.8 to 7.3 which occurred in Japan during the period 2000-2016. It should be note that for (Mjma>3) the latter agrees rather well with the seismic moment magnitude (Mw) (Edwards et Rietbrock 2009). The hypocentral location, depth and magnitude of each event are given in Table 1.

![Figure 1. Distribution of seismic sequences in data base according to magnitude](image1)

![Figure 2. Magnitude versus PGA distribution](image2)
The earthquakes were recorded by the KiK-net nationwide strong motion networks, these acceleration records have been attentively selected from the website http://www.kyoshin.bosai.go.jp, the distributions of ground motion records versus earthquake magnitude and site class are presented in figures 1 and 2. Careful selection of samples or data may significantly improve the performance of the trained neural network.

Table 1. Summary of events used in this investigation

<table>
<thead>
<tr>
<th>Origin Time</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Depth</th>
<th>Magnitude</th>
<th>Earthquake Name Or Epicenter Region</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016/04/16-07:23</td>
<td>32.79N</td>
<td>130.77E</td>
<td>012km</td>
<td>M4.8</td>
<td></td>
</tr>
<tr>
<td>2016/04/16-07:11</td>
<td>33.27N</td>
<td>131.40E</td>
<td>006km</td>
<td>M5.4</td>
<td></td>
</tr>
<tr>
<td>1998/04/22-20:32</td>
<td>35.17N</td>
<td>136.56E</td>
<td>010km</td>
<td>M5.4</td>
<td></td>
</tr>
<tr>
<td>2016/04/18-20:42</td>
<td>33.00N</td>
<td>131.20E</td>
<td>009km</td>
<td>M5.8</td>
<td></td>
</tr>
<tr>
<td>2011/03/23-07:12</td>
<td>37.08N</td>
<td>140.79E</td>
<td>008km</td>
<td>M6.0</td>
<td></td>
</tr>
<tr>
<td>2003/07/26-07:13</td>
<td>38.40N</td>
<td>141.17E</td>
<td>012km</td>
<td>M6.2</td>
<td>Northern Miyagi prefecture</td>
</tr>
<tr>
<td>2016/10/21-14:07</td>
<td>35.38N</td>
<td>133.85E</td>
<td>011km</td>
<td>M6.6</td>
<td>The Mid Niigata Prefecture Earthquake in 2004</td>
</tr>
<tr>
<td>2004/10/23-17:56</td>
<td>37.29N</td>
<td>138.87E</td>
<td>013km</td>
<td>M6.8</td>
<td>Northwest off Kyushu</td>
</tr>
<tr>
<td>2005/03/20-10:53</td>
<td>33.74N</td>
<td>130.18E</td>
<td>009km</td>
<td>M7.0</td>
<td>The Western Tottori Prefecture Earthquake in 2000</td>
</tr>
<tr>
<td>2000/10/06-13:30</td>
<td>35.28N</td>
<td>133.35E</td>
<td>011km</td>
<td>M7.3</td>
<td></td>
</tr>
</tbody>
</table>

3. SCALING OF INPUT

The normalization processing for all data used in development of the ANN is an important step; the neural network training can be made more efficient if certain preprocessing steps are performed on the network inputs and targets (Howard and Mark 1992). In addition, the values should be scaled to match the range of the input neurons. This means that along with any other transformations performed on network inputs, each input should be normalized.

Scaling of the training data is performed so that the processed data is in the range of $-1$ to $+1$. The training data sets (inputs and targets outputs) are scaled (pre-processed) according to:

$$P_n = 2 \times \frac{(P-minP)}{(maxP-minP)} - 1$$  \hspace{1cm} (1)

$$T_n = 2 \times \frac{(T-minT)}{(maxT-minT)} - 1$$  \hspace{1cm} (2)

- $P$ = matrix of the input vectors;
- $T$ = matrix of the output vectors;
- $P_n$ = matrix of scaled input vectors;
- $T_n$ = matrix of scaled target output vectors;
- $minP$ = vector containing minimum values of the original input;
- $maxP$ = vector containing maximum values of the original input;
- $minT$ = vector containing the minimum value of the target output
- $maxT$ = vector containing the maximum value of the target output.

The scaled data is then used to train the neural network. The data from the output neuron has to be post-processed to convert the data back into unscaled units to get the PGA parameter according to

$$T = 0.5 \cdot (T_n + 1) \cdot (maxT + minT) + minT$$  \hspace{1cm} (3)
4. SITE CONDITION, EPICENTRAL DISTANCE AND MAGNITUDE DISTRIBUTIONS

Site condition parameters are used to quantify the influence of local site geology on the characteristics of the ground motion. The KiK-net database provides geotechnical information on the site of each station. This information consists of the lithology description and the velocity profile for both P and S waves.

Local site effect is one of the most important aspects for engineering design and is often characterized by a set of simplified parameters, such as site class based on site predominant period (Zhao et al. 2006), site class based on geological and geotechnical description of soil layers and site period (McVerry et al. 2006), and the average soil shear-wave velocity down to a depth of 30m ($V_{s30}$) used by many recent ground motion prediction equations (GMPEs) (Abrahamson and Silva 2008), (Boore et al. 1994) (Ambraseys 1995).

In this study in addition to the $V_{s30}$, the resonant frequency $f_{800}$ is also included as a parameter to characterize the site effect on the PGA of the strong ground motion.

The $f_{800}$ and $V_{s30}$ for each site are calculated using the following equations:

$$f_{800} = \sum_{i=1}^{n} \frac{h_i}{4 \times Z_{800}}$$  \hspace{1cm} (4)

$$V_{s30} = \frac{30 \sum_{i=1}^{n} \frac{h_i}{v_i}}{h_i}$$ \hspace{1cm} (5)

Where $h_i$: the thickness of the $i^{th}$ layer; $v_i$: the shear velocity of the $i^{th}$ layer; $Z_{800}$: the depth down to a velocity of 800 m/s

Figure 3 shows the distribution of the site classes according to NEHRP classification (BSSC 2000) which is based on the shear-wave velocity $V_{s30}$. More than 65% of the strong ground motions used in this study were recorded on site class C, about 16% on site class D ($V_{s30}$ between 180 and 760 m/s) and 17.5% on site class B ($V_{s30}$ greater than 760 m/s).

The magnitudes of the selected records were evenly distributed between 4.5 and 7.5 corresponding to epicentral distances varying from 20km to 200 km as shown in Figure 4.
5. SOURCE-TO-SITE DIRECTIONALITY

Directionality of ground motion is an important aspect to be considered in earthquake engineering, many empirical relationships have been proposed in the literature to estimate the characteristics of ground motion but few of these relationships have incorporated the directionality of ground motion. An analysis of the effect of directionality is carried out. For a given set of two ground motion components (East-West and North-South) the component of ground motion corresponding to a rotational angle \( \theta \) is determined as follows: (Lee 2014) (Laouami, et al. 2006)

\[
a_{\text{rot}}(t, \theta) = a_1(t) \cos(\theta) - a_2(t) \sin(\theta)
\]

- \( \theta \): rotational angle
- \( a_1, a_2 \): orthogonal horizontal components E-W and N-S
- \( a_{\text{rot}} \): horizontal component rotated by \( \theta \)

The two as-recorded orthogonal-component time series are combined into a single time series corresponding to an azimuth given by an increment of rotation angle using the equation above. For each record the ratio between the maximum value and the recorded value in the E-W and N-S is calculated. The procedure steps are summarized below (Boore 2010):

a. Determine the characteristics (PGA value) of a horizontal component in the as-recorded orientation set as 0 degree.
b. Rotate the horizontal component by \( I \) degree using equation cited previously and determine the characteristics
c. Repeat a and b until the rotation angle reaches 180 degree
d. Determine the characteristic for all the rotation angles
e. Sort the maximum for each of the characteristics (PGA value)

The results show the effect of directionality on the PGA values, the ratio of the maximum to the minimum may reach up to 1.35 (increase of 35%).

![PGA variation according to critic direction](image)

It should be pointed out that the KYOSHIN network (i.e., KiK-net and K-NET) provides the coordinates (latitude /longitude) for the station and the seismic source as illustrated in figure 6. A directionality parameter is defined as the angle between the orientation of the epicenter-station path and the direction of the component (EW or NS). This parameter is used among other inputs in the ANN model to predict the peak acceleration of the strong ground motion.
6. ARTIFICIAL NEURAL NETWORK MODEL

An artificial neural network is a simple mathematical operator. Each neuron receives one or more inputs and sums them to produce an output. Usually the sum of each node is weighted by coefficients (known as weights of connections or synaptic weights), and the sum is passed through a non-linear function known as an activation function. There are many topologies established by different authors to define the structure of the ANN; nevertheless, in this work the FeedForward Multilayer Perceptron FMP was selected. Multilayer perceptrons have been applied successfully to solve some of the difficult and diverse problems in several domains including the structural engineering applications.

There are several functions such as hyperbolic tangent, sigmoid and linear functions that can be used as transfer function. The type of activation function plays an important role. This function allows the introduction of nonlinearity in the network and therefore allows a better modeling of complex phenomena. The results show that the configuration with a hyperbolic tangent function for the hidden layer and for the output layer gives the best results. According to the above provisions, inputs to the network are defined here by the values of magnitude ($M_{\text{mag}}$), epicentral distance ($R_{\text{epi}}$), shear-wave velocity ($V_{s30}$), resonant frequency ($f_{800}$), the focal depth ($d$) and the angle epicenter-station ($\theta$). The output node is represented by peak ground acceleration PGA (Figure 7). A standardization of all data was performed to improve the performance of the model.

![Figure 6. Radial angle “Od” for two components of AKTH02 station during 26-07-2003 earthquake M=6.2](image)

![Figure 7. Input/Output of ANN models](image)
A total of 1104 values have been divided into three sets:
The training set, which is about 70% of the complete database, has been used to train the network; the validation set, which is about 15%, has been used for the purpose of monitoring the training process, and to guard against overtraining; and the testing set, which is about 15%, has been used to judge the performance of the trained network. The training was stopped when the cross-validation error began to increase, i.e., when the cross-validation error reached a minimum, the training should be stopped.
The selection of the optimal architecture of an ANN is not an easy task as it is necessary to test a large number of architectures to achieve the best one. In this paper a large number of architectures were tested using various parameters in order to obtain the best ANN model. The format for the architecture arrangement is detailed in section 7.1 with assessment values given in table 2 and 3.
The performance of the developed neural network models is carried out by comparing the target PGA and those predicted by the models. Figure 8 shows the regression curves for all data (1104 samples) which reveal a coefficient of correlation R equal to 0.86.

\[ e_i = \log_{10}\left(\frac{\text{obsPGA}_i}{\text{prePGA}_i}\right) \]  

(7)

Where: obsPGA\(_i\) and prePGA\(_i\) are the recoded and predicted PGA.

The residuals are plotted against the epicentral distance, the magnitude and the focal depth as shown on Figure 9. The plots are pretty symmetrically distributed, tending to cluster towards the middle of the plots showing no bias or trend in the residuals in any of these plots.
7. RESULTS AND DISCUSSIONS

7.1 Neural network topology optimization

As it was described before, to determine the optimal architecture of an ANN it was necessary to test a large number of neural topologies. Table 2 and 3 show the results and the activation function used for the layers and list for each configuration the correlation coefficients related to each subset: training, validation and test ($R_{\text{train}}$, $R_{\text{valid}}$ and $R_{\text{test}}$).

The accuracy of the prediction is evaluated by comparing the performance criteria; Table 3 shows the performance of the four ANN architectures, along with their respective prediction accuracy. On one hand it is observed that the best value of correlation coefficient ($R$) with small value of Mean Square Error (MSE) is associated with the combinations ($\tanh$-$\text{sigmoid}$ – $\tanh$-$\text{sigmoid}$) as a function activation, on the other hand it has been found that the neuron number considered of the hidden layer have approximately same prediction accuracy which mean that the number of neurons used in the hidden layer has no influence on the performance of this particular models. This table lists the MSE and $R$ for different tests using different combinations. Following various tests on the different combination and architecture used it can be concluded that the PGA predicted by the ANN with six inputs using the combination of activation function ($\tanh$-$\text{sigmoid}$ – $\tanh$-$\text{sigmoid}$) with ten neurons has been found to be more accurate.
7.2 Effect of magnitude, epicentral distance and soil velocity on the peak ground acceleration

The PGA is plotted against epicentral distance on Figure 10. It can be noticed that the trend of the variation of the PGA is more sensitive to the magnitude and is almost decreasing with distance. As illustrated in figure 10 comparisons are made between the predicted PGA in three types of site: A site characterized by a shear-wave velocity $V_{S30}=200\text{m/s}$ ($f_{800}=1.67\text{Hz}$ soft soil) and the other one characterized by a shear-wave velocity $V_{S30}=800\text{m/s}$ ($f_{800}=6.68\text{Hz}$ Rock site). This figure shows clearly for both cases that the PGA decreases with the distance. It can be noted that the soft soil ($V_{S30}=200\text{m/s}$; $f_{800}=1.67\text{Hz}$) produces more than 50% greater PGA value than those on the rock site.
8. SENSITIVITY ANALYSIS

A sensitivity analysis for the input variables was performed in order to quantify the influence of each parameter on the PGA. Percentages of synaptic weight, $P_i$, that correspond to each of the five parameters were computed using the following equation (Derras 2012):

$$P_i = \frac{\sum_{j=1}^{Nh} |w_{ij}|}{\sum_{i=1}^{N} \sum_{j=1}^{Nh} |w_{ij}|}$$

(8)

Where: $w_{ij}$: synaptic weights of the ANN; $1 \leq i \leq 6 \text{ and } 1 \leq j \leq 10$
Nh: number of hidden neurons Nh=10; N: number of input variables N=6
This analysis was conducted for the models developed and the overall results are summarized in Figure11. As can be seen on this figure, the inputs parameters have almost the same effects on the PGA except that the soil frequency parameter $f_{800}$ which has less influence.

![Figure 11. Input sensitivity analysis for PGA](image)

9. CONCLUSION

The prediction of the peak ground acceleration for a given site is of paramount importance in many practical applications of earthquake engineering. In this paper a neural network based method has been used to predict the peak acceleration for a given set of seismological parameters. The main features of the proposed model are:

- The elaborated model has six input factors: the magnitude ($M_{jma}$), the epicentral distance ($R_{epi}$), the shear-wave velocity ($V_{s30}$), the resonant frequency ($f_{800}$), the focal depth (d) and the angle epicenter-station ($\theta$).
- A large number of ground motions extracted from the KiK-net strong motion database were used to train the ANN and the performance criteria was used to assess the accuracy of the predictions and found that the configuration with hyperbolic tangent function for both hidden layer and output layer gives the best PGA predictions and can reach a level of correlation coefficient equal to 0.86.
- Based on the residuals analysis the results show that the fit of the developed models to the recorded data set appears reasonable and the residuals curves are free of any trend with respect to any of explanatory variables.
- The PGA increases with magnitude and decreases with increasing distance and $V_{s30}$ (stiffer sites), these observations are consistent with those shown in previous studies.
- A new input parameter called “radial angle $\theta$” associated to each seismic component is introduced explicitly instead of the conventional method based on geometric mean or the maximum of the two orthogonal components.
- On the basis of a sensitivity analysis, it can be concluded that all input parameters are comparably influencing the PGA including the newly introduced parameter $\theta$. 

10
• Finally, from a practical perspective, the ANN model with only one hidden layer and a limited number of neurons, makes it easy to implement it in a spreadsheet or a simple computer program using the synaptic matrices and the bias vector (presented in annexes), so that it can be routinely integrated in engineering applications and for probabilistic seismic hazard analysis (PSHA) studies.

10. REFERENCES


11. ANNEXES

Synaptic weight matrices and bias vectors of the ANN model.

\( w_1 \): Nh\times N matrix of synaptic weights, Nh: input parameters and N: number of hidden neurons.

\( w_2 \): Vector of size Nh that contains the synaptic weights between the hidden layer and the single-output parameter.

\( b_1 \), \( b_2 \): The bias vectors of the hidden layer and output layer.

**Model: PGA**

\[ w_1 = 
\begin{bmatrix}
1.1483 & -1.6031 & 0.91218 & 0.048856 & -0.56716 & -0.64599 \\
0.10273 & 0.42777 & -0.36178 & 0.057407 & -0.12529 & -0.27508 \\
-1.727 & 0.38588 & 2.0824 & -0.486 & 0.1813 & -0.48307 \\
1.3525 & -0.67121 & 0.92101 & -1.5773 & -0.016869 & -1.4048 \\
-0.59759 & 0.19538 & 1.0443 & 0.097137 & 0.085263 & -1.6796 \\
-1.206 & -1.1835 & 1.5556 & -0.70775 & -0.67736 & 0.68444 \\
-0.42559 & -0.35528 & 0.24135 & 0.83902 & 0.2252 & 1.67 \\
-0.37471 & 0.92767 & -1.6935 & -0.82764 & 0.61669 & -0.98461 \\
0.90866 & 0.21944 & -0.8056 & 1.6722 & 0.45942 & 0.4847 \\
0.40843 & 0.74955 & -1.2999 & -0.54665 & 0.74894 & -0.74042 \\
\end{bmatrix} \]

\[ b_1 = [-1.9878; -0.53903; 2.3438; -0.37136; -0.99748; 0.58767; -0.59632; 1.2691; 1.4337; 2.3942] \]

\[ w_2 = 
\begin{bmatrix}
-0.38069 & 2.3815 & -0.58706 & -0.41775 & -0.30508 & 0.4202 & -0.61476 & -0.32847 & 0.0023957 & -0.38659 \\
\end{bmatrix} \]

\[ b_2 = [-0.79503] \]