A METHOD FOR PREDICTION OF PEAK HORIZONTAL ACCELERATION BY ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In this study, a model on the basis of artificial neural networks is developed to predict the peak horizontal acceleration. The neural network model provides an objective analysis method which requires neither specifying predictive functional forms nor the independence of the inside variables. The Joyner and Boore data set (1981), was used for analysis. For comparison, one- and two-step regression procedures were also applied to the same data set. Various fitness criteria have been considered, and the analysis of residuals were also conducted to evaluate the analytical results. Finally, the proposed procedure showed an agreeable capability for the required prediction of ground motion parameters, and has advantage such as less complexity, less mean square error and higher coefficient of determination when compared to the conventional methods.

KEYWORDS

Earthquake hazard; Peak horizontal acceleration; Regression analysis; Neural network; Prediction.

INTRODUCTION

Seismic hazard evaluation is commonly based on empirical predictive relations. Such relations are generally expressed as mathematical functions connecting a strong motion parameter to the parameters characterizing the earthquake source, the propagation path distance and the local site conditions. The most important aspect for mitigation of earthquake hazard is the prediction of strong motion parameters, likely at a particular site.

One of the special features of the earthquake ground motion, which is of considerable interest to engineers and seismologists, is the maximum peak value of ground acceleration developed at any specific site during an earthquake. During the past few decades several attempts have been made to estimate the peak acceleration with various pertinent properties of the strong motion records, *e.g.* Gutenberg & Richter, 1956; Housner, 1969; Trifunac, 1976; Campbell, 1989; *etc.*. In order to predict the peak horizontal acceleration, various analytical procedures have been introduced by researchers so far. Among these, regression analysis has been widely used with different techniques, *e.g.* Donovan, 1973; Joyner & Boore, 1981; Campbell, 1981; Fukushima & Tanaka, 1990. Since the 1970s, numerous empirical relations of dependence of peak acceleration magnitude and distance have been presented, *e.g.* Esteva, 1970; where reference to many others can be found in the review articles by Joyner, 1987; Joyner and Boore, 1988; and Anderson, 1991a. Hitherto , all of the above-mentioned published studies use parametric models.

In an exploratory data analysis, Brilinger and Preisler (1984) have applied two different techniques to the Joyner and Boore (1981) data for prediction of the peak horizontal acceleration. Carr and Glass (1989) applied the so-called Krieging, a technique of geostatistics which is commonly used to estimate mineral resources, to

interpolate the peak acceleration. A nonparametric empirical description was adopted by Anderson and Yutain (1994) to estimate the peak acceleration.

In general, regression analysis is a technique for fitting curves (linear or nonlinear surfaces) to data points. Sympson (1992) points out that the nodal function used in many error correction learning algorithms of neural networks is a family of curves, and the adjustment of the weights that minimizes the overall mean-squared error is equivalent to curve fitting. In this sense, the back-propagation algorithm is an example of an automatic nonlinear regression technique. With this notion, neural networks could be applied to the predictive issues in earthquake engineering.

In this study a model on the basis of artificial neural networks with the back-propagation algorithm is developed to estimate the peak horizontal acceleration. Neural network models provide an objective analytical outlook which requires neither specifying predictive functional forms nor the independence of the inside variables. The inside variables, for example earthquake magnitude and distance, are somehow related in the observed data, despite their theoretical independence from each other. This fact has a negative effect on the prediction based on the conventional regression procedures. To improve traditional regression procedures (one-step regression), new procedures, *e.g.* Joyner and Boore (1981), has been developed to overcome this problem by introducing the so-called two-step regression procedure. In our model, this complexity resulting from the dependence of the inside variables, has no impact on the estimation of the peak horizontal acceleration.

In this paper, in order to demonstrate the potential capability of the neural network models in predicting the peak horizontal acceleration, three different analytical procedures - the conventional regression method (one-step procedure), the Joyner and Boore (1981), method (two-step procedure), and a neural network model - have been applied, and compared with each other. The uncertainty involved in the prediction of the peak horizontal acceleration was examined through the analysis of residuals.

THE DATA

To demonstrate the reliability of the artifial neural network model for prediction of the peak horizontal acceleration, the Joyner and Boore data set (1981) was used in this study. A broad variety of functional forms for such data have been proposed by Joyner and Boore (1981), Bolt and Abrahamson (1982), and Brillinger & Preisler (1984).

The data set consists of 182 recordings of the peak acceleration from 23 earthquakes, and is restricted to shallow earthquakes in the western North America with moment magnitudes M_W greater than 5.0. The number of records for each event vary, with six events having but one record. The magnitude of the earthquakes ranges between 5 and 7.7, but most of the earthquakes are in the range 5.5 to 6.5. The distance in which the data are obtained ranges from less than 1 km to 300 km. This distance is defined as the closest distance to the fault rupture in kilometers. The larger of the peak horizontal accelerations of two components is selected in each case.

ANALYTICAL PROCEDURES

The aforementioned three analytical procedure - *i.e.* the single- and two-step regression analyses (1981), and also the nonparametric neural network approach developed in this article - are examined for the selected data to estimate the peak horizontal acceleration. A conventional regression analysis begins by assuming the form of the analytical expression for the peak acceleration ($A_{max.}$) as a function of magnitude (M) and distance (R), and possibly other parameters. The analysis then estimates unknown coefficients in this equation which minimize the average misfit of observation.

Regression analysis has important limitations. First, it requires a formal expression and second, its inside variables should be fully independent from each other. The latter is of considerable importance from the analytical point of view. Therefore, some functional forms and regression procedures have been introduced so far to reduce the effect of the coupling between magnitude and distance dependence (*e.g.*, Joyner and Boore, 1981). On the other hand, neural network models provide an analytical method which requires neither a functional form nor the independence of variables. Such models are based on the function of biological neurons (Rumelhart *et al.*, 1986).
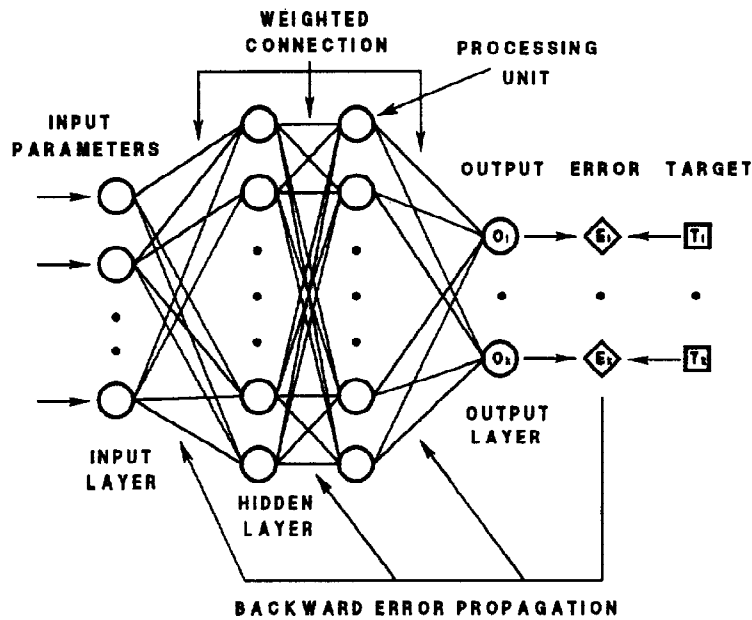
Fig.1. The structure of a typical multilayer neural network with
back-propagation error correction.

An artificial neural network consists of a large number of simple processing units called nodes. These nodes are interconnected in a parallel architecture, with varying degrees of strength as indicated by their connection weights. A typical neural network is organized into several layers: an input layer, one or more hidden layers, and an output layer. Each layer is made up of one or more nodes or units. Moreover, there might be an arbitrary number of intermediate or hidden layers, each containing an arbitrary number of neurons. The number of the hidden layers and their nodes would be selected during an effort of trial and error. Neural networks vary in physical design, training model and functionality. A detailed presentation of the neural network theory can be found in the Zeidenberg, (1990). Fig.1 illustrates a typical architecture of a multilayer neural network with back-propagation error correction that consists of an input layer, two hidden layers, an output layer, and three levels of adaptive connections.

The classic back-propagation learning algorithm of neural networks was used in our analysis to train a feed-forward network for prediction of the peak horizontal acceleration. The ability of this learning method to automatically capture nonlinear mapping is significant. The back-propagation learning algorithm uses a least squares error minimization criterion to minimize the error. This can be accomplished by adjusting the weights according to the negative gradient of the error with respect to the weights. Rumelhart et al., (1986) provide a detailed description of back-propagation learning algorithm in their article.

Analysis and interpretation of neural network behavior is inherently difficult due to the high dimensionality of the solution space. Recent research (e.g. Dennis and Phillips, 1991; Hutton, 1992; Ripley, 1992; has focused on the use of nonparametric and parametric statistical techniques to analyze and interpret the neural network behavior. It has been shown that a forward-chained, multilayer network using a back-propagation learning algorithm is mathematically equivalent to a nonlinear least squares regression fit of the data (Golden, 1988).

Our network model consist of three layers with twelve sigmoidal nodes in the hidden layer and a sigmoid output unit. Inputs to the network are the earthquake magnitude and distance with three additional combinations. Peak horizontal acceleration is expressed as the logarithm of acceleration (cm/s^2) which was normalized according to minimum and maximum values, and was considered as a target. The input data to the network were also normalized based on minimum and maximum values of each input parameter in order to homogenize the weight values. The network has been examined through many training procedures to find out the suitable structure, and finally to get better adjustment for the root-mean-square error cost function. Based on the data shown
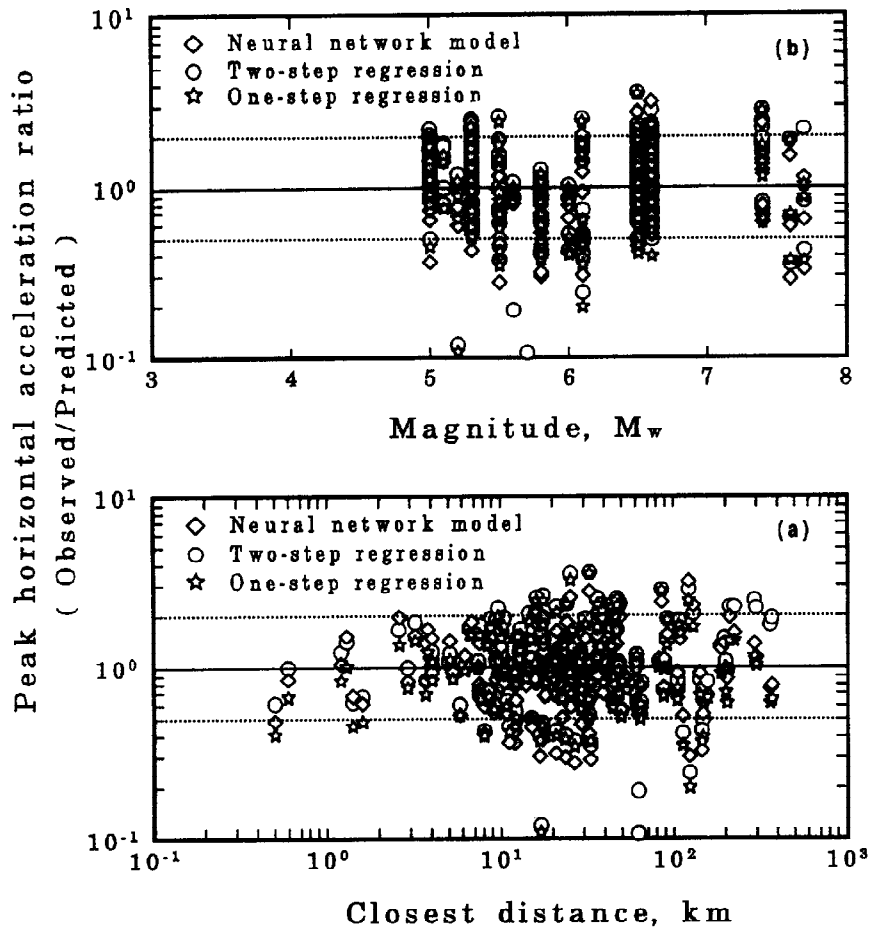
Fig.2. Plots of residuals as functions of distance (a) and magnitude (b),
according to three analytical procedures.

Prediction curves of the neural network model for magnitudes 6.0 and 7.0 are compared with results of the one-
and two-step regression analyses in Fig.3. As can be deduced from this Figure, the neural network model is in
good agreement with the observed data. For distances less than 10 km, the estimation from one-step regression
appears at higher values than other two models, while the estimated acceleration of our model is nearly similar
to that of Joyner and Boore (1981). We point out that the graphs prepared by Joyner and Boore (1981) and
our study, in the case of M=6.0 and 7.0, show that the curves do not differ dramatically. Fig.4, is constructed
in accordance with our proposed neural network model, and might be used to estimate the peak horizontal
acceleration.

CONCLUDING REMARKS

The main purpose of this paper was to point out that the neural network model can be directly applied to
the earthquake ground motion data. The performance of the neural network model in estimating the peak
accelerations can be evaluated from the results of this study. This evaluation proves that our approach is
capable to predict earthquake ground motion parameters.

A general advantage of this method is that no commitment has been made to prespecified functional forms. Our
approach is an objective analytical method which dose not require the independence of estimator parameters,
an important condition in conventional analytical procedures. Considering the set of the data used, it is possible
to show the ultimate superiority of the neural network model over conventional predictive methods.

Table 1. The variation in the estimation error with changes in the number of inputs (a)
and hidden unites (b).

a) Number of inputs	Coefficient of determination	Mean square error	b) Number of hidden unites	Coefficient of determination	Mean square error
2	0.8124	0.049	8	0.8148	0.048
3	0.8145	0.048	10	0.8148	0.048
4	0.8153	0.048	12	0.8125	0.048
5	0.8125	0.048	15	0.8106	0.049
			18	0.8080	0.050
			20	0.8062	0.050

Table 2. Fitness criteria and their values for various analytical procedures.

Analytical method	Mean square error	Standard error of estimation	Coefficient of determination	δ_{logY}
Neural network model	0.05	0.22	0.81	0.47
One step regression	0.06	0.25	0.76	0.45
Two step regression (Joyner & Boore, 1981)	0.06	0.25	0.77	0.48

in Table 1 (a & b), the fitness error due to variation in the number of input and hidden units, 12 units were chosen for the hidden layer. The proposed network provides an unlimited flexibility to describe complicated magnitude and distance dependencies.

RESULTS AND DISCUSSION

To evaluate the accuracy of the analytical models, several statistical parameters are calculated, such as the correlation of determination (R^2), mean-square-error (MSE) and standard error of estimation (SEY). The fitness results of analysis for applied methods are given in Table 2. The results show that the neural network model is comparable with, and partly superior to the conventional methods. A correlation of determination (the measure of the goodness of fit) of 0.81 is achieved for the neural network model. In comparison, for the Joyner-Boore data (1981), the correlation of determination values of 0.76 and 0.77 are found for the one- and two- step regression procedures, respectively.

In order to test for potential biases in the prediction regarding magnitude, distance or predicted accelerations, plots of the residuals with respect to these three parameters were carefully inspected. The residual was simply defined as the ratio of the observed to predicted values. Two examples of these plots appear in Fig.2 (a and b). If there were systematic trends in the data not accounted for by our statistical analysis, it should be evident from these plots. However, the residuals were found to be uniformly distributed with respect to magnitude , distance, and the predicted accelerations. A correlation analysis confirmed that the residuals were uncorrelated regarding to these variables.

Neural networks can effectively provide an accurate estimate if there is reasonable correlation between input and output data. However accuracy is limited by the available data. Since the neural network system is sensitive to the distribution of training data, the best results can be obtained if the data is well distributed over the magnitude and distance range.
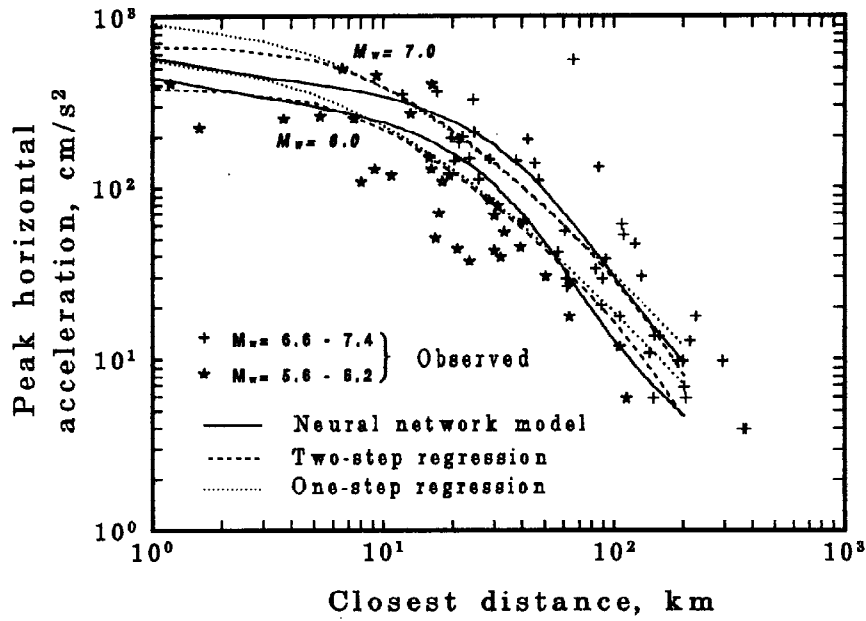
Fig.3. Observed peak horizontal acceleration and model- based predictions for
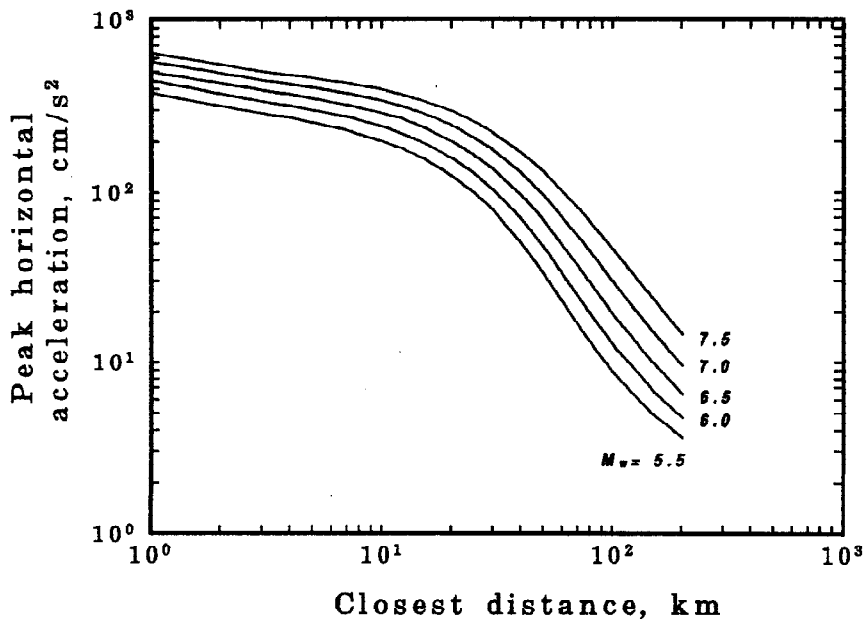magnitude 6 and 7.

Fig.4. Predicted values of peak horizontal acceleration as a function of distance
and moment magnitude, using the neural network model.

Finally, we conclude that the model has the capability for prediction of other ground motion parameters such
as estimation of velocity, displacement and acceleration response spectra. The neural network method will be
extended to these notions in our future studies.

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