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Prediction of principal ground-motion parameters using a hybrid method coupling artificial neural networks and simulated annealing

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ABSTRACT

In this study, new models are derived to predict the peak time-domain characteristics of strong ground-motions utilizing a novel hybrid method coupling artificial neural network (ANN) and simulated annealing (SA), called ANN/SA. The principal ground-motion parameters formulated are peak ground acceleration (PGA), peak ground velocity (PGV) and peak ground displacement (PGD). The proposed models relate PGA, PGV and PGD to earthquake magnitude, earthquake source to site distance, average shear-wave velocity, and faulting mechanisms. A database of strong ground-motion recordings released by Pacific Earthquake Engineering Research Center (PEER) is used to establish the models. For more validity verification, the ANN/SA models are employed to predict the ground-motion parameters of a part of the database beyond the training data domain. ANN and multiple linear regression analyses are performed to benchmark the proposed models. Contributions of the input parameters to the prediction of PGA, PGV and PGD are evaluated through a sensitivity analysis. The ANN/SA attenuation models give precise estimations of the site ground-motion parameters. The proposed models perform superior than the single ANN, regression and existing attenuation models. The optimal ANN/SA models are subsequently converted into tractable design equations. The derived equations can readily be used by designers as quick checks on solutions developed via more in-depth deterministic analyses.

1. Introduction and background

Seismic hazard analysis is an essential step in engineering phase. The seismological characteristics of earthquakes usually include magnitude, distance, faulting type, and soil effects. Time-domain and response-domain parameters are well-known engineering parameters of an earthquake. Three major parameters of the time-domain class are: (1) peak ground acceleration (PGA), (2) peak ground velocity (PGV), and (3) peak ground displacement (PGD) [1]. The time and response-domain parameters can both be applied to structural risk assessment. The spectral parameters are shown to be more efficient than the time-domain parameters [2]. On the other hand, the time-domain parameters are more practical due to their independency from structures. Thus, PGA, PGV and PGD are frequently used in seismic hazard studies. These key elements can be predicted using different methods such as on-site investigation and physical modeling. In most cases, implementing these methods is extensive, cumbersome and costly [1,3]. Much effort should be made to describe limited observations through the physical modeling of an earthquake. The physical models are usually developed in the context of stochastic modeling approach and random vibration theory [4]. More advanced physical modeling methods simulate the realistic process of faulting through the numerical analysis of crack and wave propagation [5].

An empirical approach to assess the ground-motion engineering parameters is to use attenuation relationships. The attenuation relationships play a key role in seismic hazard analysis. They often correlate the ground-motion parameters with various independent variables (e.g., earthquake magnitude, distance from source to site, local site conditions, and earthquake source characteristics) [1,3,6]. It is not an easy task to develop a correlation between PGA, PGV and PGD and the predictor variables due to high nonlinearity in the relationships. Regression analysis is a conventional way to build the attenuation relationships from the recorded strong motion data [7–10]. In this context, Fajfar and Perus [11] proposed a non-parametric multidimensional regression method for the prediction of the seismic ground-motion parameters. Perus and Fajfar [12] used a non-parametric approach, called conditional average estimator (CAE) method, for the ground-motion prediction. In addition to physical aspects [5,13], the commonly used regression analysis has major drawbacks related to the idealization of complex processes, approximation, and averaging widely varying prototype conditions. Also, the nature of the corresponding problem should be pre-defined by a linear or nonlinear equation to perform the regression analysis [1]. Thus, the derived attenuation models

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are often limited in their ability to efficiently simulate the complex behavior of the ground-motion parameters [2]. The issues raised above suggest the necessity of utilizing more robust methods to predict the ground-motion parameters.

Empirical modeling by artificial intelligence techniques, such as genetic programming (GP) and artificial neural networks (ANNs), is a different approach to estimate the ground-motion characteristics. Such methods have a great capability of adaptively learning from experience and extracting various discriminators. Recently, Cevik and Cabalar [14] utilized a branch of GP, namely gene expression programming (GEP) to derive a greatly simplified prediction equation for PGA upon a strong ground-motion data from Turkey. Gandomi et al. [1] presented a hybrid method coupling GP and orthogonal least squares, called GP/OLS, to derive new ground-motion prediction equations. Kerh and Chu [15] employed ANNs to predict PGA at two main line sections of Kaohsiung Mass Rapid Transit in Taiwan. Chu et al. [16] developed an ANN model to analyze the strong motion characteristics around the Kaohsiung area of Taiwan. Kerh and Ting [17] used ANNs to predict PGA along a high-speed rail system in Taiwan. Gullu and Ercelebi [3] and Gunaydin and Gunaydin [18] developed prediction models for PGA using ANNs upon a strong motion database from Turkey. Ahmad et al. [19] established ANN-based attenuation relationships for PGA, PGV and PGD using the European earthquake data. A major constraint in application of ANN is the network's tendency to become trapped in local minima [20]. To cope with this problem and to obtain an optimal solution, a neural network may be trained using global search algorithms such as genetic algorithms [21,22], tabu search [23] and evolutionary strategies [24]. Simulated annealing (SA) has also been used by researchers [25–27] for training ANNs as an alternative to the more traditional local search algorithms (e.g., gradient search techniques). Recently, Ledesma et al. [28] combined ANNs and SA to make a hybrid algorithm with better efficiency. They proposed a novel cooling schedule based on temperature cycling for implementing SA to improve the ANN training. It was shown that the networks trained using temperature cycling outperformed those trained by the conventional exponential or linear cooling schedules [28]. Despite remarkable prediction capabilities of this hybrid ANN/SA method [28], there has not been yet any scientific efforts directed at applying it to civil engineering tasks.

In this study, the ANN/SA technique is utilized to derive new generalized attenuation relationships for PGA, PGV and PGD. The employed hybrid system uses the SA strategy to assign good starting values to the weights of the network before performing optimization. ANN/SA is useful in deriving prediction models for PGA, PGV and PGD by directly extracting the knowledge contained in the experimental data. ANN-based models are commonly considered as black-box systems as they are unable to explain the underlying principles of prediction. To overcome this limitation, the optimal ANN/SA models are converted into relatively simple design equations. A conventional calculation procedure is further proposed based on the fixed connection weights and bias factors of the best obtained structures. The predictions made by the developed models are further compared with those provided by the ANN, regression and empirical models [7,10,29]. The proposed models are developed based on a comprehensive database of strong ground-motions assembled by Pacific Earthquake Engineering Research Center (PEER) [30].

2. Methodology

2.1. Artificial neural network

ANNs have emerged as a result of simulation of biological nervous system. The ANN method was founded in the early 1940s by McCulloch and co-workers [31]. The first researches were focused on building simple neural networks to model simple logic functions. ANNs can be applied to a variety of problems without algorithmic solutions or problems with complex solutions. ANNs formulate a mathematical model for a system in which no clear relationship is available between inputs and outputs. Multilayer perceptron (MLP) network [32] is the most well-known class of ANNs. MLPs have feed-forward architectures. They are essentially capable of approximating any continuous function to an arbitrary degree of accuracy [32]. These networks are usually applied to perform supervised learning tasks, which involve iterative training methods to adjust the connection weights within the network [33]. They are usually trained with back-propagation algorithm. Fig. 1 shows a schematic representation of an MLP network. The MLP network consists of an input layer, at least one hidden layer of neurons and an output layer. Each of these layers has several processing units and each unit is fully interconnected with weighted connections to units in the subsequent layer. Each layer contains a number of nodes. Every input is multiplied by the interconnection weights of the nodes [33]. Finally, the output (h_j) is obtained by passing the sum of the product through an activation function as follows:

$$h_j = f\left(\sum_i x_i w_{ij} + b\right) \quad (1)$$

where $f(\,)$ is activation function, x_i is the activation of ith hidden layer node, w_{ij} is the weight of the connection joining the jth neuron in a layer with the ith neuron in the previous layer, and b is the bias for the neuron. For nonlinear problems, the sigmoid functions (hyperbolic tangent sigmoid or log-sigmoid) are commonly adopted as the activation function. Adjusting the interconnections between layers will reduce the following error function [34,35]:

$$E = \frac{1}{2}\sum_n \sum_k \left(t_k^n h_k^n\right)^2 \quad (2)$$

where t_k^n and h_k^n are respectively the calculated output and the actual output value, n is the number of sample and k is the number of output nodes. Further details of MLPs can be found in [32].

2.2. Simulated annealing

SA is a general stochastic search algorithm used for solving optimization problems. This algorithm was first applied to optimization problems by Kirkpatrick et al. [36] and Cerny [37]. SA is very useful for solving several types of optimization problems with nonlinear functions and multiple local optima [38,39]. SA makes use of the Metropolis algorithm [38] for computer simulation of annealing. Annealing is a process in which a metal is heated to a high temperature and thereafter it is gradually cooled to relieve thermal stresses. During the cooling process, each atom takes a specific position in the metal crystalline structure [40]. By changing the

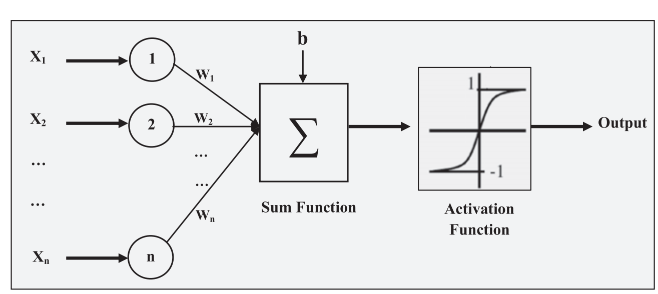

Fig. 1. A schematic representation of an MLP neural network.