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Research paper

Prediction of peak ground acceleration of Iran's tectonic regions using a hybrid soft computing technique

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ABSTRACT

A new model is derived to predict the peak ground acceleration (PGA) utilizing a hybrid method coupling artificial neural network (ANN) and simulated annealing (SA), called SA-ANN. The proposed model relates PGA to earthquake source to site distance, earthquake magnitude, average shear-wave velocity, faulting mechanisms, and focal depth. A database of strong ground-motion recordings of 36 earthquakes, which happened in Iran's tectonic regions, is used to establish the model. For more validity verification, the SA-ANN model is employed to predict the PGA of a part of the database beyond the training data domain. The proposed SA-ANN model is compared with the simple ANN in addition to 10 well-known models proposed in the literature. The proposed model performance is superior to the single ANN and other existing attenuation models. The SA-ANN model is highly correlated to the actual records ($R = 0.835$ and $\rho = 0.0908$) and it is subsequently converted into a tractable design equation.

1. Introduction and background

Peak ground acceleration (PGA) is a well-known engineering parameter of an earthquake, which can be applied to seismic structural analysis and risk assessment. This key element can be predicted using different methods such as physical modeling and on-site investigation (Alavi and Gandomi, 2011). However, implementing such a method is extensive, cumbersome and costly and, most of the time, is impossible (Gullu and Ercelebi, 2007; Gandomi et al., 2011).

An approach to assess the PGA is to use attenuation relationships which play a key role in seismic analysis. They usually formulate the PGA with various independent variables such as distance from the source to site, earthquake magnitude, local site conditions, and earthquake source characteristics (Kramer, 1996; Gullu and Ercelebi, 2007; Gandomi et al., 2011). Developing a correlation between the PGA and the predictors is difficult due to high complexity and nonlinearity.

Soft computing has been widely used to resolve a variety of classification or prediction problems in science, medicine and engineering (e.g. Yaghouby et al., 2010a, 2012). Artificial neural network (ANN) as a commonly used predictor in soft computing mimics the network structure of actual human brain and has been applied to several classification or prediction problems (Yaghouby et al., 2009). This empirical modeling tool has a great capability of adaptively learning from experience and extracting various correlations. This soft computing technique, ANN, has been widely utilized for geotechnical engineering modeling in the last two decades (e.g. Goh, 1994; Azmathullah et al., 2005; Das and Basudhar, 2008; Samui and Sitharam, 2010; Gandomi and Alavi, 2011; Guven et al., 2012; Fister et al., 2014) and have recently been used to predict ground motion characteristics (e.g. Gullu and Ercelebi, 2007; Ahmed et al., 2008; Cevik and Cabalar, 2009; Alavi and Gandomi, 2011; Alavi et al., 2011; Gandomi et al., 2011). A major constraint in application of ANN is the network's tendency to become trapped in local minima (Hamm et al., 2007). To obtain an optimal solution and avoiding this problem, an ANN may be trained using global optimization algorithms (e.g. Das et al., 2011). Ledesma et al. (2007) have recently combined ANN and a well-known derivatively-free global optimization algorithm named simulated annealing (SA) to improve the ANN efficiency. They used a new cooling schedule based on temperature cycling for implementing SA. It was shown that the networks trained using temperature cycling outperformed those trained by the conventional exponential or linear cooling schedules (Ledesma et al., 2007; Alavi and Gandomi, 2011).

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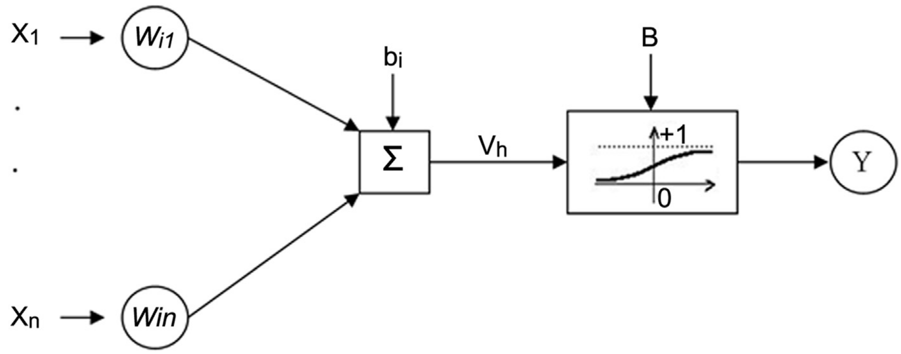

Figure 1. A basic representation of an MLP neural network.

In this study, the SA-ANN technique is used to derive an explicit formula for the PGA. In the hybrid algorithm, SA strategy is used to assign initial starting values to the weights and biases of the network before performing ANN. The SA-ANN system can derive a prediction model for PGA by directly extracting the knowledge contained in the experimental data. An ANN model is usually considered as a black-box system; therefore it cannot be used later. To deal with this issue, the optimal SA-ANN-based model is converted into an explicit equation. The results obtained by the developed model are further compared with those provided by the 10 other models proposed in the literature. The proposed model is developed based on a comprehensive database of strong ground-motion recordings of 36 earthquakes.

2. Methodology

2.1. Artificial neural network

McCulloch and co-workers founded the ANN method in the early 1940s (Perlovsky, 2001). ANNs is a predictive tool to build a mathematical model for an unknown system. Multi-layer perceptron (MLP) ANN (Cybenko, 1989) is the most well-known class of ANNs and usually has feed-forward architectures. The MLPs are usually trained with back-propagation algorithm. The MLP network consists of one input and one output layer, and at least one hidden layer. Each of these layers has a number of nodes and contains processing unit(s) and each unit is fully interconnected with weighted connections (w_{ij}) to subsequent layer units (Alavi et al., 2010). The output (Y) is obtained by passing the sum of the product through an activation function. Fig. 1 shows a basic representation of an MLP ANN. In this figure X_i shows the inputs and b/B shows the biases between different layers.

For complex and nonlinear problems, the hyperbolic tangent function or sigmoid function (or log-sigmoid) can be adopted as the activation function.

2.2. Simulated annealing

SA is a global search algorithm used for solving optimization problems, which makes use of the Metropolis algorithm (Metropolis et al., 1953) for computer simulation of annealing. This algorithm was initially used for optimization problems by Kirkpatrick et al. (1983). SA is very useful for solving nonlinear problems with multiple local optima (Aarts, 1989). When a metal is heated to a high temperature and thereafter it is gradually cooled to relieve thermal stresses is called annealing. The cooling process is simulated by SA to optimize a function in a certain design space. The objective function relates the energy state and moving to any different set of design variables corresponds to changing the crystalline structural state (Gandomi et al., 2013). The abilities and shortcomings of SA are well summarized by Ingber (1993).

2.3. Hybrid artificial neural network-simulated annealing

A hybrid computational approach could be optimized by combining more than one soft computing technique in an efficient way so that the final model would outperform original one in a specific problem (e.g. Yaghouby et al., 2010b; Gandomi and Alavi, 2013). An ANN can be trained from a set of data known as a training set. During the training process, the network's weights are optimized until reaching the stop criteria. The training procedure has two main steps including initialization and optimization (Alavi and Gandomi, 2011). In the initialization process initial values to the weights of the network are assigned. The initial weights can be

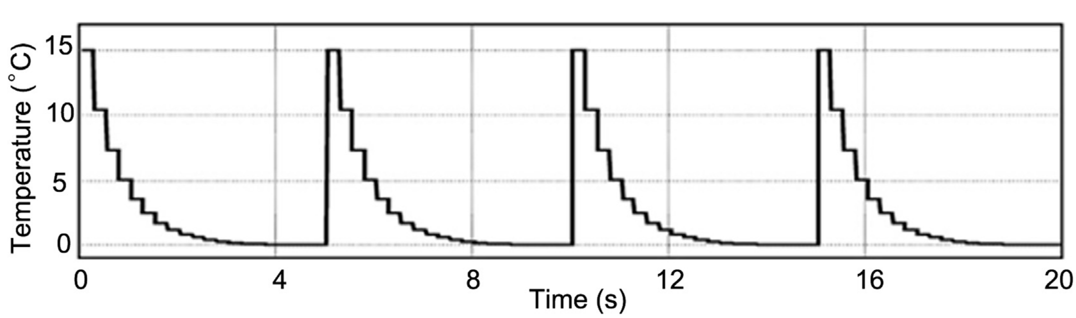

Figure 2. Temperature cycling (after Ledesma et al., 2007).