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Shear wave velocity and soil type microzonation using neural networks and geographic information system

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A R T I C L E I N F O

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A B S T R A C T

Frequent casualties and massive infrastructure damages are strong indicators of the need for dynamic site characterization and systematic evaluation of a site's sustainability against hazards. Microzonation is one of the most popular techniques in assessing a site's hazard potential. Improving conventional macrozonation maps and generating detailed microzonation is a crucial step towards preparedness for hazardous events and their mitigation. In most geoscience studies, the direct measurement of parameters imposes a huge cost on projects. On one hand, field tests are expensive, time-consuming, and require specific high-level expertise. Laboratory methods, on the other hand, are faced with difficulties in perfect sampling. These limitations foster the need for the development of new numerical techniques that correlate simple-accessible data with parameters that can be used as inputs for site characterization. In this paper, a microzonation algorithm that combines neural networks (*NNs*) and geographic information system (*GIS*) is developed. In the field, standard penetration and downhole tests are conducted. Atterberg limit test and sieve analysis are performed on soil specimens retrieved during field-testing. The field and laboratory data are used as inputs, in the integrated *NNs-GIS* algorithm, for developing the microzonation of shear wave velocity and soil type of a selected site. The algorithm is equipped with the ability to automatically update the microzonation maps upon addition of new data.

1. Introduction

Casualties and massive infrastructure destruction are great indicators of the need for systematic characterization of a site's sustainability against natural disasters. Microzonation has been known as one of the most accepted tools in assessing soil failure potentials. Seismic microzonation is a generic name for the process of subdividing a seismic-prone area into zones based on appropriately selected geotechnical properties. This process can be done by systematically estimating the response of soil layers to earthquake excitations. The result of a microzonation process is a geographical map—generated in terms of suitable geotechnical and geophysical parameters—illuminating specific geological characteristics of a site, such as soil type, or the potential of different zones of a site for geotechnical failures, such as ground shaking, liquefaction, landslide, tsunami, and flooding. One example parameter that can be used in microzonation is the small-strain shear modulus (also called maximum shear modulus, G_{max}). G_{max} can be correlated to the deformation potential of a given site against seismic actions. This parameter has been discovered to have a direct correlation with the small-strain shear wave velocity of a soil [1]. In other words, shear wave velocity in low strains can be used as a unique and reliable parameter that can be used in microzonation maps.

Making improvements on the traditional macrozonation maps and generating detailed microzonation maps is a crucial step towards preparedness for future hazardous events. In the last few decades, efforts were made to perform microzonation on different earthquake-prone areas to be used for construction and design purposes. Fäh et al. [2] carried out a detailed microzonation of the city of Basel to perform a numerical modelling of expected ground motions during earthquake events. Tuladhar et al. [3] performed a seismic microzonation for the city of Bangkok by using micro-tremor observations. Anbazhagan and Sitharam [4] mapped the average shear wave velocity for the Bangalore region in India. They also proposed an empirical relationship between the Standard Penetration Test blow count (*SPT-N*) and shear wave velocity. Vipin et al. [5] carried out a performance-based liquefaction potential analysis based on *SPT* data acquired from Bangalore, India. Cox et al. [6] presented a seismic site classification microzonation of the city of Port-au-Prince based on shear wave velocity of the soil and provided a code-based classification scheme for the city. Murvosh et al. [7] carried out shear wave velocity profiling in complex ground to

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enhance the existing microzonation of Las Vegas. Kalinina and Ammosov [8] studied the applicability of multichannel analysis of surface waves to address the solutions for microzonation problems.

For a good microzonation, it is not only important to obtain reliable data from field measurements but also to identify and implement a robust technique to optimize the input-output relationship. Most of the statistical methods require a significant volume of data to produce reliable results. Direct measurement of most geotechnical parameters imposes huge costs on projects. Field tests are time-consuming and need specific expertise. Laboratory methods, on the other hand, are faced with difficulties from imperfect sampling. These limitations necessitate the development of numerical techniques that correlate easily accessible data with parameters that require extensive effort. In light of this, Artificial Intelligence (*AI*) integrated with *GIS* can be used to model the seismic hazard susceptibility of a site.

Fuzzy Networks, metaheuristic algorithms, and most importantly, neural networks (*NNs*) can all be categorized under the field of *AI*. *NNs* are designed to approximate complicated non-linear correlations between input and output layers of a specific problem while using a small fraction of data for training purposes [9–11]. Furthermore, *NNs* are designed to eliminate the complicated statistical variables that exist in conventional statistical methods [12]. The integration of *NNs* with *GIS* has recently been tried for various problems [13]. Li and Yeh [14] used this approach to simulate multiple land use changes in southern China. Pijanowski et al. [15] proposed a model to evaluate the land transformation. Lee et al. [12] used an integrated *GIS* and *NNs* to study the landslide susceptibility in the area of Yongin in Korea. Pradhan and Lee [16] analyzed the regional landslide hazard utilizing optical remote sensing data. Yoo and Kim [17] predicted the tunneling performance required in routine tunnel design works. Pradhan et al. [18] proposed a *GIS*-based neural network model to obtain landslide susceptibility mapping for risk analysis. Ho et al. [19] proposed a methodology to assess the water leakage and prioritize the order of pipe replacement in a water distribution network.

In this study, *NNs* have been used to correlate easily obtainable geotechnical parameters with parameters that govern the seismic potential of a soil. The resulting correlation has been implemented in generating microzonation maps. Python coding has been implemented to develop a dynamic system capable of automatically improving microzonation maps as additional data is acquired and inserted. The proposed algorithm has been applied for the microzonation of Urmia City, which is located in the northeastern part of Iran. In the succeeding sections of the paper, the design and implementation of an integrated system that performs geotechnical microzonation of a site will be presented.

2. Methods and materials

2.1. Neural networks (NNs)

Neural networks are known to be the main and inspiring branch of artificial intelligence. It is not an overstatement to claim that the word intelligence is an appropriate attribute for neural networks, since the *NNs* algorithms are based on simplified mathematical models for the interconnected electro-chemical transmitting neurons, what we call it "Brain" [20]. *NNs* are designed to extract non-linear correlations between effective variables by examining a large set of responses. Neural networks are primarily trained with a large data set. *NNs* are able to provide accurate output for a data set if a proper training plan has been implemented. Correctly, designed *NNs* will have three main parts: the transfer function, the network structure, and the learning law. These parts are defined separately based on the type of the defined problem [21].

NNs consist of an interaction between several interconnected nodes, called artificial neurons. These neurons exchange messages with each other. These neurons could be located in several different layers. The structure of designed *NNs* includes three different types of layers: (1) input layer (2) hidden layer(s) and (3) output layer. Each structure has one input layer and one output layer. Hidden layers are intermediate layers defined between the input and output layers where the active signals are transmitted between layers. The number of hidden layers and nodes per layer are set based on trial and error by the network's designer. The connections between neurons have numeric weights that can be adjusted based on experience. This feature helps the *NNs* learn from experience. Each weighted neuron connection is activated by a transform function in a given layer. This process is repeated until the output neurons are all activated. The error of the *NNs* is defined as the difference between the *NNs* output and the given observation. The weights are then changed until the error is minimized. The minimization of the error can be performed with different types of optimization techniques. Metaheuristic methods such as the harmony search algorithm have been used in several engineering problems [22,23]. Least squares methods can also be used to minimize the error.

From a number of different types of *NNs*, a feedforward network is selected here. Such a network uses backpropagation (*BP*) technique—a gradient descent algorithm in which the network weights are moved along the negative of the gradient of the performance function. In this study, the Levenberg-Marquardt (*LM*) algorithm [24] is employed to optimize the weight of networks. This algorithm has the capability of solving non-linear least squares problems. For the basic *BP* algorithm, the weights of the network are adjusted in the direction that the rate of descent for the performance function is highest. The weight of the network for each iteration is calculated from the following expression:

$$\mathrm{W}_{k+1} = \mathrm{W}_k - \alpha_k \mathrm{G}_k \tag{1}$$

where W_k is a vector of current weights, G_k is the current gradient, and α_k is the learning rate.

For fast optimization, the gradient can be replaced by the Hessian matrix of the performance index at the current values of the weights ($\mathbf{A}_k^{-1}$). Since a huge computational effort is required to obtain the Hessian matrix for feedforward neural networks, the *LM* algorithm has been designed to approach a second-order training speed without the need to calculate the Hessian matrix [25]. For the performance function with the form of a sum of squares, the Hessian matrix can be approximated by:

$$\mathbf{H} = \mathbf{J}^{\mathrm{T}}\mathbf{J} \tag{2}$$

$$\mathrm{G} = \mathbf{J}^{\mathrm{T}}\mathrm{E} \tag{3}$$

where **J** is the Jacobian matrix that contains the first derivatives of the network errors with respect to the weights, and E is a vector of network errors.

The Jacobian matrix can be computed through a standard backpropagation technique [25] which bypasses the difficulty of computing the Hessian matrix. The *LM* algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$\mathrm{W}_{k+1} = \mathrm{W}_k - [\mathbf{J}^{\mathrm{T}}\mathbf{J} + \mu\mathbf{I}]^{-1}\mathbf{J}^{\mathrm{T}}\mathrm{E} \tag{4}$$

The correction factor μ is a counterweight that guarantees the reduction of the performance function. Any increase or decrease in performance function is accompanied by mutual increase or decrease in the correction factor. This way, the performance function is always reduced at each iteration of the algorithm [26].

Overfitting is the most common problem that may occur during the training process. This problem occurs when the obtained error for the training set of the data is very small but that of the testing data is very large. The network has memorized the training examples, but it has not learned to generalize to new situations (i.e., testing data). Regulation is a technique that prevents overfitting and improves network generalization. It involves modifying the performance function, which is normally chosen to be the sum of squares of the network errors in the training set.