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Interevent times estimation of major and continuous earthquakes in Hormozgan region based on radial basis function neural network

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ABSTRACT

This paper presents a new method to estimate the time of important earthquakes in Hormozgan region with magnitude greater than 5.5 based on the Radial Basis Function (RBF) Neural Network (NN) models. Input vector to the network is composed of different seismicity rates between main events that are calculated in convenient and reliable way to create optimized training methods. It helps network with a limited number of training data to estimation. It is common for earthquakes modeling by data-driven methods in this case. In addition, the proposed method is combined with Rosenberg cluster method to remove aftershocks events from the history of catalog for NN to better process the data. The results show that created RBF model successfully estimates the interevent times between large and sequence earthquakes that can be used as a tool to predict earthquake, so that comparison with other NN structure, for example Multi-Layer Perceptron (MLP) NN, reveals the superiority of the proposed method. Because of superiority proposed method has higher accuracy, lower costs and simpler network structure.

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1. Introduction

The earthquake is a natural phenomenon caused by the sudden release of energy stored in the ground created by seismic waves. Earthquakes occur naturally due to the nature of tectonic motions [1,2]. Earthquakes cause ground displacement and in some cases trigger a tsunami, it should be noted that in some cases, human activities are effective in occurrence of earthquakes. Forecasting and prediction in many cases are synonymous, but have the subtle difference. The present work is prediction [3]. Over time there have been significant efforts in earthquake prediction. Earthquake prediction is an interdisciplinary field of research in seismology, physics, geology, mathematics, computer science, engineering, and even social sciences. The US National Academy of Science defines earthquake prediction as the estimation of any one or more parameters of a future earthquake, namely, time of occurrence, epicentral location, and magnitude. Earthquake prediction studies can be categorized into two types, one is based on the analysis of earthquake precursor data, and the other is based on the analysis of historic earthquake data. Important earthquake precursors include changes in the earth's electromagnetic field [4], abnormal animal behavior [5,6], seismic quiescence [7], fault creep and continuous strain [8–10], and anomalous geochemical observations [11,12]. Changes in seismicity patterns are the most successful long-term precursors. Studies based on historical earthquake data often attempt to establish a magnitude–frequency relationship. The most popular distributions are the Gutenberg-Richter inverse power law distribution [13]. One of the hardest but best searching methods is the use of new and emerging accounting principles, such as Neural Networks (NNs) and evolutionary computation are particularly suited to solving complex problems. In general, the time scale earthquake prediction according to interval of the impending earthquake is classified as short, medium and long-term. The long-term prediction of natural disaster occurrence is one of the most sought-after goals in geoscience. Succeeding in such a goal involves obviating a multitude of difficulties; not only the proper variables which will act as precursors should be recognized and measured, but also the correlations between those variables and disaster occurrence should be identified. In spite of the significant progress over the last 20 years [14–16], the determination of such correlations remains a difficult endeavor as the governing relationships are usually rather complex and nonlinear, and the mechanisms creating the respective correlations are only recently coming to be understood [17,18].

Seismicity databases (catalogs) are the most popular source of data for long-term prediction studies for a number of reasons (including: abundance, existence for almost all regions of the world, availability on a continuous basis). On the other hand, NNs are powerful mathematical tools [19] that simulate the way that the human brain deals with information and the procedure of learning. Recently, efforts have been made to investigate the potential of Artificial Neural Networks (ANNs) as a tool for system behavior simulation that are governed by nonlinear multivariate and generally unknown interconnections within a noisy, poorly-controllable physical environment. The choice of the ANN approach is motivated by the lack of clear causal relations between seismicity patterns and related crustal environments. In addition, the smart methods have higher precision, lower cost and easier calculations than traditional and classical methods. It seems attractive to us considering the seismicity rates, because many seismologists share the view that changes in seismicity rates can occur as part of the process of preparation for large earthquakes [19,20]. Therefore, during the early 1980's the impact of man-made effects on seismicity rates was demonstrated for the first time [7].

2. Geological setting of studied region

Hormozgan region is in north of the Strait of Hormuz in southern Iran, and is one of the most strategic parts of the world politically and economically. Coastal zones of the region are on the east of Oman. The historical record confirms that some areas, for example, Zagros and Makran, in terms of seismicity are active of 2500 years ago, and this reflects the long-term nature of seismicity areas [21]. Hormozgan region as shown in Fig. 1 is located inside the interface between the geographical coordinates 25°24′N to 28°57′N and 53°41′E to 59°15′E from Greenwich meridian [22].

3. Neural networks

Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) NNs are briefly explained in this section.

3.1. *RBF Neural networks*

RBF network is a kind of forward NNs composed of three layers including input layer, hidden layer and output layer. Each of these layers has different roles, respectively [23]. In RBF networks, outputs are determined by calculating the distance between network inputs and the centers of the hidden layer. The second layer is a hidden linear layer, and outputs of this layer weight bearing samples from the outputs of the input layer. Each hidden layer neuron with a vector parameter called the center. Therefore, a general description of the network is given by equation (1) [24]:

$$\hat{y} = \sum_{i=1}^{I} wi\phi(\|\mathbf{x} - ci\|) + \beta \tag{1}$$

Standard mode is usually the Euclidean distance, and RBF is intended with Gaussian function as equation (2):

$$\varphi(r) = \exp\left(-\alpha i\|\mathbf{x} - ci\|^2\right) \tag{2}$$

In equations (1) and (2), the following definitions are considered: $i \in \{1, 2, 3, \ldots, I\}$, so I is the number of neurons in the hidden layer; w_i, weight between neuron in the hidden layer and output; φ, Gaussian function; α_i, spread parameter (amount of variance) neuron; $\mathbf{x}$, input data vector; c_i, center vector of neuron; β, bias of output; $\hat{y}$, output of the network.

Fig. 2 shows the schematic overview of a RBF network. M-dimensional inputs ($x_1, \ldots, x_m$) are placed in the input layer.