QUID 2017, pp. 1137-1142, Special Issue N°1- ISSN: 1692-343X, Medellín-Colombia

STUDY OF RISK ANALYSIS AND EARTHQUAKE MAGNITUDE AND TIMING PREDICTION VIA TECTONIC AND GEOTECHNICAL PROPERTIES OF THE FAULTS AND IDENTIFYING RISKY AREAS IN TERMS OF SEISMICITY IN LARESTAN CITY USING ARTIFICIAL NEURAL NETWORK

(Recibido el 29-06-2017. Aprobado el 18-09-2017)

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Resumen: De acuerdo con las encuestas sismo-tectónicas realizadas en la ciudad de Larestán y considerando las fallas que causaron los terremotos ocurridos, se estudia una red utilizando una red de redes neuronales artificiales, capaz de predecir el momento y la magnitud del terremoto. Todos los parámetros de entrada, incluyendo la profundidad focal, la distancia entre el epicentro del terremoto y la falla causante, la magnitud del terremoto y la magnitud del terremoto se normalizaron primero y se usaron en el software como entrada. Por último, se calculó el momento de los futuros terremotos y la cantidad de energía que se disipaba de la tierra en ese momento analizando los resultados.

Palabras clave: gestión de crisis, red neuronal artificial, análisis de riesgo, sismicidad

Abstract: According to the seismo-tectonic surveys performed in Larestan City and considering the faults causing the earthquakes happened, a network is studied using artificial neural network technique, which is able to predict the timing and magnitude of the earthquake. All input parameters, including focal depth, the distance between earthquake epicenter and the causative fault, earthquake timing, and earthquake magnitude were first normalized and used in the software as input. Finally, the timing of future earthquakes and the amount of energy to be dissipated from the earth at the time were calculated by analyzing the results.

Keywords: crisis management, artificial neural network, risk analysis, seismicity

Citar, estilo APA: Cheraghi, A. & Ghanbari, A. (2017). Study of risk analysis and earthquake magnitude and timing prediction via tectonic and geotechnical properties of the faults and identifying risky areas in terms of seismicity in Larestan city using artificial neural network. *Revista QUID (Special Issue).* 1137-1142.

1. INTRODUCTION

Earthquake prediction is considered as one of the most important tools in crisis management. That's why seismic surveys are necessary to be performed in seismic zones. According to the seismo-tectonic surveys in Larestan City and considering the faults causing the earthquakes happened, a network is studied by the information obtained from the available accelerometers and using artificial neural network technique which is able to predict the timing and magnitude of earthquake in the area under study (Larestan City). In this research, different data sets were used to train and test artificial neural network by choosing a statistical procedure, and the results obtained were analyzed. The analysis result determined the amount of dissipated energy exerted on the earth by a certain date.

2. INPUT INFORMATION AND ARTIFICIAL NEURAL NETWORK MECHANISM

In artificial neural network method, a known set of input data and their corresponding outputs in the system are used for training the network (training set data). Similarly, some data are used to test the network (test set data) (Asim, Martínez-Álvarez, Basit & Iqbal, 2016). In such processes, the network control parameters gradually converge to their final values after implementing training and test set data. There are some tools in designing neural networks which manage the network training procedure. Figure (1) shows a view of Thinks Pro software, in which the training data are shown in the upper table, the test data are shown in the lower table, and the error values are shown in the right hand side of the figure.

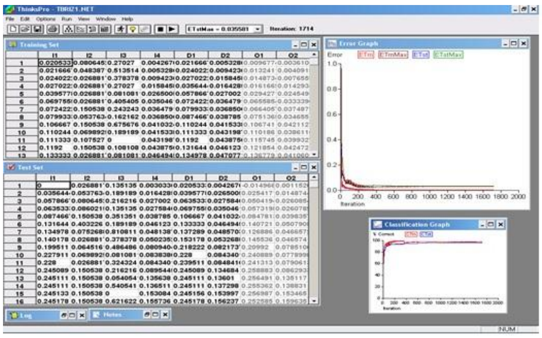

Figure 1. shows a view of Thinks Pro

All network inputs should be normalized, so that the network would be able to identify, distinguish, and classify the data, and finally be able to have a correct training from the patterns. Equation (1) is used for normalization.

$$x_{normalized} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \qquad (1)$$

where $x_{normalized}$ is the normalized data, x is the non-normalized data, $x_{\min}$ is the minimum data, and $x_{\max}$ is the maximum data in the data set.

Figure (2) shows the input, output, and hidden layers of the artificial neural network.

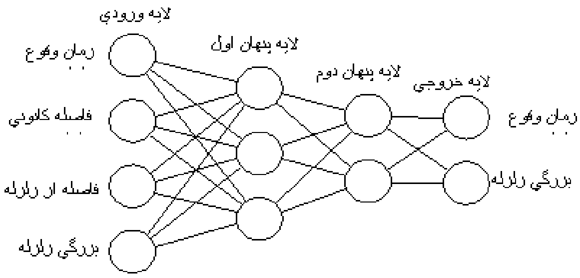

Figure 2. shows the input, output, and hidden layers of the artificial neural network

One of the important problems in the seismic studies is finding the relationship between different earthquake components. Equation (2) represents the relationship between the energy released and the earthquake magnitude, experimentally introduced by Richter and Gutenberg (Kasim, Korkmaz, Fuat Demir, 2016).

$$Log_{10}E = 11.8 + 1.5M \qquad (2)$$

where E is earthquake vibration energy (erg), and M is the magnitude of shallow earthquakes.

An artificial neural network is used in this study via Think Pro software with the following characteristics:

1. Forward multilayer network (MNP)
2. Back error propagation learning algorithm (BPN)
3. Sigmoid stimulating function
4. Mean Square Error

In order to use the software, the test set data were separated from the training set data. In this study, the data extracted from the database, including 908 data in chronological order, were utilized, 30% of which were used as test data, and the remaining were used as training data. The process of selecting the optimal network arrangement should be in a way that facilitates achieving final goal and produces a lower error. The networks' capabilities were compared and evaluated based on the available information in order to select the training algorithm.

The data used in this study were:

A. Earthquake Timing: The time of earthquake was extracted from the earthquake database as the day and hour submitted for occurring the earthquake (Ting-Yu Hsu, Rih-Teng Wu & Kuo-Chun Chang, 2016). This information was available from 1900 to 2008. They were cumulatively considered from a reference time, normalized, and used.

B. Earthquake Focal Distance: The focal distances of the earthquakes occurred were available in the earthquake statistics, and were normalized based on Equation (1).

C. Distance from the Causative Fault: Given the earthquake epicenter, its distance from the closest faults was considered as the distance from the causative fault.

D. Earthquake Magnitude: The information available in the earthquake statistics was earthquake magnitude in Richter. In order to use the values obtained in the data analysis, they were transformed into energy released due to the earth activities by Equation (2), and their cumulative values during the investigation period was calculated, normalized, and used.

Network training algorithm, backward propagation and transfer function, bilinear sigmoid, error calculation method, absolute mean value, initial noise 0.001 and learning rate of the first hidden layer, second hidden layer, and output layer was 0.4, 0.03, and 0.01, respectively. The momentum of first hidden layer, second hidden layer, and output layer was also selected to be 0.02, 0.01, and 0, respectively. The statistics of test and training records was selected by random, using a computer-aided program. The Think Pro software was used to analyze the data. After 5000 iterations, the training and test mean error and maximum error was estimated to be 0.00531, 0.00567, 0.2661, and 0.0331, respectively.

3. CONCLUSION

The network designed had real input and output and was able to predict the output. A network in which the real output and the predicted output have the minimum difference is more appropriate. These results are given below in two sub-sections: earthquake magnitude and timing prediction.

3-1. Earthquake magnitude prediction

Figure (3) shows the results of comparing the normalized data of the cumulative energy released from the earth during the investigation with the values predicted. It is clear that valued predicted by the tests reasonable match with the real values available. The average network error for the test data was 0.000545, or 0.5%, and the maximum error was 0.0355, or 3.5%. Figure (4) shows the same information with normalized values. In this figure, the cumulative energy released by different earthquakes occurred consecutively is compared with the predicted values. For example, this figure shows that is the cumulative energy released from the reference time (1900) to a certain time is 50,000 million ergs, what will be its predicted value. It is clear from the figure that predicted cumulative energy released by earth is very precise. Figure (5) shows the cumulative energy released by earth versus time. In this figure, the predicted valued of energy are compared with the measured values.

For example, this figure shows that the cumulative energy released by earth 2500 days after the reference time is 54,500 million ergs, and its predicted value is 54,520 million ergs, which are reasonable match. Figure (6) compares the magnitude of the earthquakes occurred and the magnitude of predicted earthquakes in Richter. In this figure, the earthquakes magnitude is estimated based on the cumulative energy released by earth. The comparison values indicate the earthquake prediction is fairly match with the real values occurred.

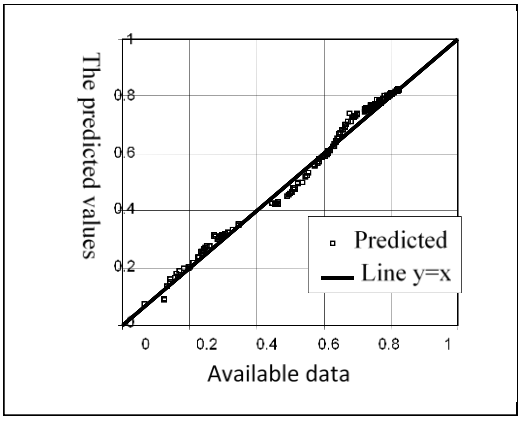

Figure 3. Comparison of the normalized predicted values of earth released energy during earthquake with the existing data

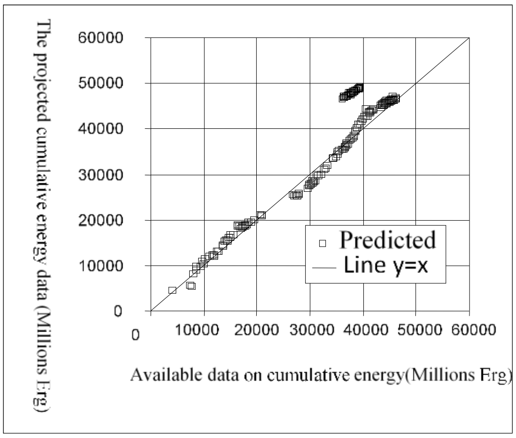

Figure 4. Comparison of the normalized predicted values of earth released energy during earthquake with the existing data

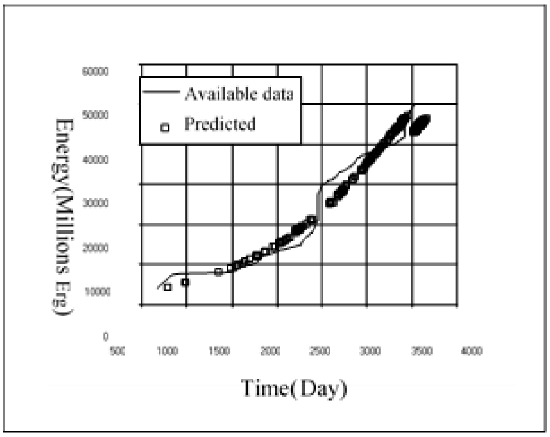

Figure 5. Comparison of the normalized predicted values of earth released energy during earthquake with the existing data

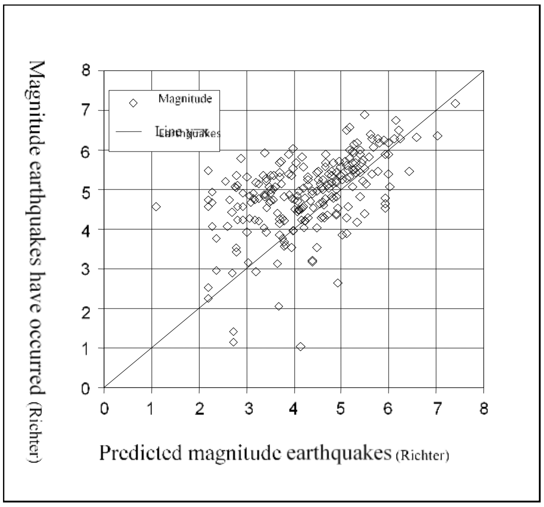

Figure 6-The comparison of the magnitude of predicted earthquake (in Richter) with occurred earthquakes in San Francisco

3.2. Earthquake timing prediction

Figure (7) shows the normalized values of earthquake timing prediction for network test data. The test errors are similar to the information given in section (6-1). Figure (8) shows the earthquake timing prediction with respect to the reference time (1900). For example, it can be said that the timing of the earthquake occurred 3500 days from the reference time is predicted to be 3510 days, which has 10 days error.

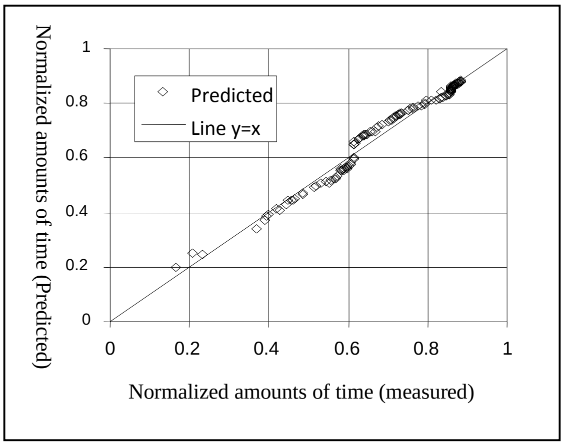

Figure 7. The comparison of the normalized results of the time of predicted earthquake occurrence with measured earthquake

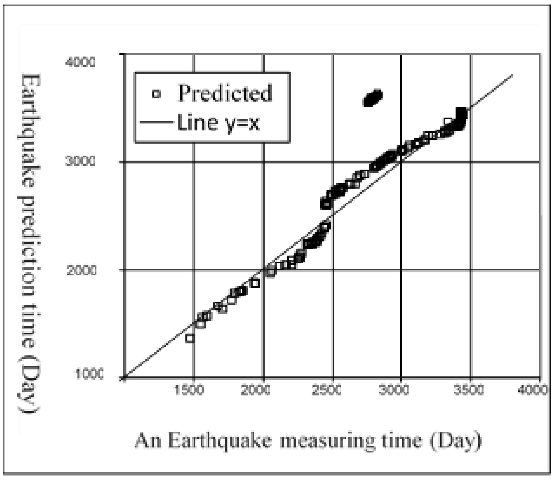

Figure 8. The results of prediction of the time of earthquake occurrence to the origin time (1973)

4. FUTURE EARTHQUAKE PREDICTION

In this study, earthquake timing with respect to the reference time and the amount of energy released from the earth were investigated. It means that using this method, the cumulative energy to be released from the earth during the next 6 months, for example, can be predicted. Whether this amount of energy is released at once or gradually is also predictable to some extent, but the most important point is that based on the amount of energy releases during the past three months, it can be estimated that how much energy is there in the earth, which has to be released. The importance of this point is that is small earthquakes don't occur during a few months, the magnitude of the probable earthquake which might happen in future can be predicted. The same is true about earthquake timing. In order to predict future earthquake timing and magnitude in the artificial neural network presented, the amount of energy released from the earth in different times has to be normalized and introduced to the network test section as input.

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