AN ARTIFICIAL NEURAL NETWORK TO PREDICT EARTHQUAKE IN SOME PARTS OF HORMOZGAN PROVINCE

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ABSTRACT

In this paper a new earthquake prediction system is presented. This method based on the application of artificial neural networks (Adeli and Panakkat, 2009), has been used to predict earthquake s in three regions (Bandar Abbas zone, Minab zone, Hajiabad zone) in Hormozgan Province. For the three Hormozgan Province's seismic regions examined, with epicenters placed on meshes with dimensions 0.5˚ × 0.5˚. Although several works claim to provide earthquake prediction, an earthquake prediction must provide, according to (Allen, 1982), the following information:

1. A specific location or area. 2. A specific span of time. 3. A specific magnitude range. 4. A specific probability of occurrence.

That is, an earthquake prediction should state when, where, how big, and how probable the predicted event is and why the prediction is made (Dimer de Oliveira 2012) and (Marzocchi and Zechar 2011). Unfortunately, no general useful method to predict earthquakes has been found yet. This study exposes the results obtained when the proposed ANN's were applied to the sets representing the three seismicity Hormozgan Province analyzed. These sets can be downloaded from the Site of University of Tehran (IRSC, 2007). First, the type of predictions performed by the ANN is introduced. Then, the results for every area are summarized in terms of the quality parameters described in full paper. The prototypes predict an earthquake every time the probability of an earthquake of magnitude larger than a threshold is sufficiently high. The threshold values have been adjusted with the aim of obtaining as few false positives as possible. The accuracy of the method has been assessed in retrospective experiments by means of statistical tests and compared with well-known machine learning classifiers. The high success rate achieved supports the suitability of applying soft computing in this field and poses new challenges to be addressed.

INTRODUCTION

Hormozgan Province in Southern Iran (Fig.1) has several major faults (Fig.2). These faults have caused more than 880 earthquakes from 1930 to 2007 (Fig.3). The most significant event with magnitude of 7 occurred in Hormozgan province in 1977. The majority of the earthquakes occur either near plate boundaries or near faults in tectonic plates (IIEES 2003, BHRC 2005, and IRSC 2007) and Seismotectonic provinces are examples of candidate places for occurrence of future earthquakes (Nowroozi, 1976).

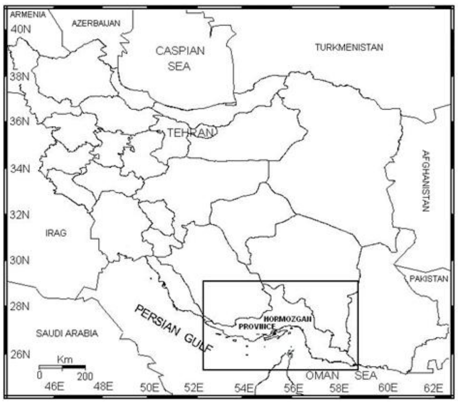

Figure 1. Map of the Hormozgan Province (Kalantari et al., 2001).

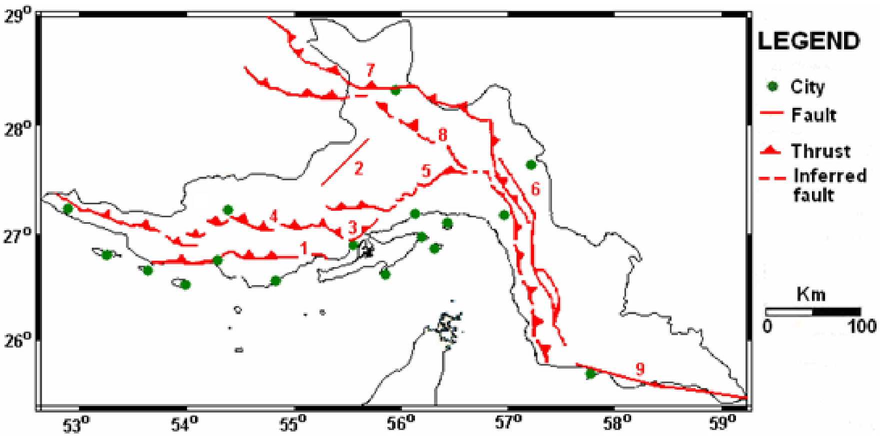

Figure 2. Major faults of Hormozgan Province (Kavei, 2003).

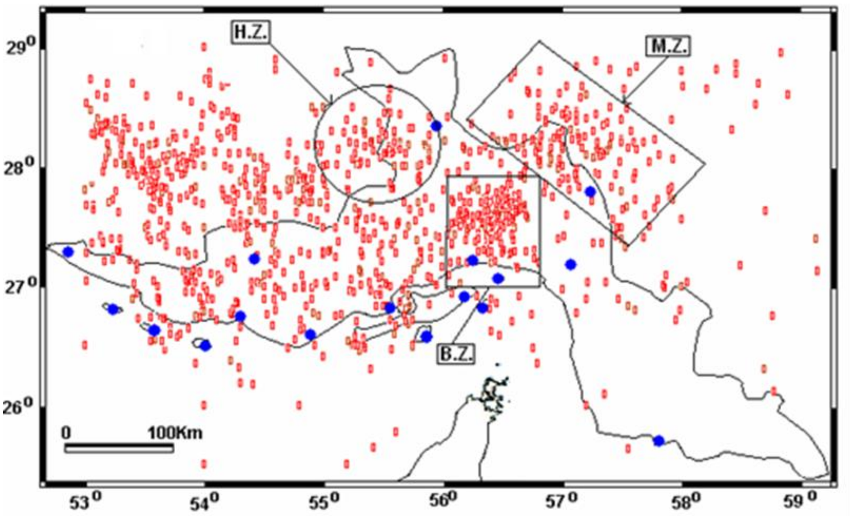

Figure 3. Epicenters of earthquakes (red points) with magnitude 2.8 - 7.0 (1930 – 2007) in the study area. The three earthquake zones, namely, Bandarabbas zone (B.Z.), Hajiabad zone (H.Z.) and Minab zone (M.Z.) are marked. Blue points denote locations of cities in the study area.

Despite forecast and predictions are used as synonymous in many fields, there are subtle differences, as discussed in (Marzocchi and Zechar 2011). In this sense, it has to be pointed that this work is about earthquake prediction. Given a set of inputs, a prediction consists in the interaction of such inputs through laws or well defined rules such as thermodynamic, rigid body mechanics, etc. As a result, the future has to be calculated with a high degree of accuracy as kinematics describes the trajectory of a projectile. In seismology the input values correspond to the stress point to point and the asperities or plates sub-topography, which are almost impossible to obtain. The data base of earthquakes used in this paper has been obtained from the Hormozgan's National seismologycall service. In order to calculated the b-value (Okal and Romanovicz ,1994) the data base must be complete. The Hormozgan earthquake data base only contains earthquakes of magnitude equal or larger to 3.0.

ANN APPLY TO PREDICT EARTHQUAKES IN SOME PARTS OF HORMOZGAN PROVINCE

Table 1 shows the ANN's configuration for predicting earthquakes in Hormozgan province.

Table1. Common features in ANN's

Parameters	Values
Input neurons	7
Neurons in hidden layer	15
Output neurons	1
Activation function	Sigmoid shape
Topology of the network	Feed forward
Learning paradigm	Back propagation

One neural network has been used for each seismic area. Note that these areas are tagged accordingly to the main city existing in their area of interest or cells: Bandar Abbas zone, Minab zone and Hajiabad zone. Although one different ANN has been applied to each area, they all share the same architecture. Note that all the for ANN's have been constructed following the scheme discussed and successfully applied in Perez and Reyes (2006), where this method used such and ANN configuration to predict atmospheric pollution. Every time an earthquake occurs at the cell subjected to analysis a new training vector, composed of seven inputs and one output, is created. First, the Gutenberg-Richter law's b-value Eq. (1) is calculated using the last 50 quakes recorded (Nuannin, 2006):

$$b_i = \frac{\log(e)}{\left(\frac{1}{50}\right)\sum_{j=0}^{49} M_{(i-j)} \; -3} \tag{1}$$

Where M_i is the magnitude for the ith earthquake and three is reference magnitude, M_0. Then, increments of b are calculated Eqs.(2,3,4,5,6):

$$\Delta b_{1i} = b_i - b_{i-4} \equiv x_{1i} \tag{2}$$

$$\Delta b_{2i} = b_{i-4} - b_{i-8} \equiv x_{2i} \tag{3}$$

$$\Delta b_{3i} = b_{i-8} - b_{i-12} \equiv x_{3i} \tag{4}$$

$$\Delta b_{4i} = b_{i-12} - b_{i-16} \equiv x_{4i} \tag{5}$$

$$\Delta b_{5i} = b_{i-16} - b_{i-20} \equiv x_{5i} \tag{6}$$

From these equations it can be concluded that 70 earthquakes are required to calculate the x_i value s, therefore, to obtain the five of the ANN inputs. The sixth input variable, x_{6i} is the maximum magnitude Ms from the quakes recorded during the last week in the area analysis. The use of this information as input is to indirectly provide the ANN's with the required information to model Omori/Utsu (1961) and bath's laws (1965).

$$x_{6i} = \max(Ms), \text{ when } t \quad [-7, 0) \tag{7}$$

Where the time t is measured in days. The last input variable, $x_{7i,}$ identifies the probability of recording an earthquake with magnitude larger or equal to 6.0. The addition of this information as input is to include

Gutenberg-Richter's law in a dynamic way as shown Eq. (8). It is calculated from the probability density function (PDF):

$$x7i = P(Ms \geq 6.0) = 10^{-3bi} \quad (8)$$

Finally, there is one output variable, y_i, which is the maximum magnitude M_s observed in the cell under analysis, in the next five days. Note that Y_i has been set to 0 for such situations where no earthquake with magnitude equal or greater to 3, $M_s \geq 3$ was recorded. Formally Eq. (9):

$$Y_i = \text{Max}\,[M_s]\ , \text{when } t \in (0, 5] \quad (9)$$

where the time t is measured in days. Mathematically, the training vector associated to the ith earthquake can be expressed as Eq. (10):

$$T_i = \{x_{1i}, x_{2i}, x_{3i}, x_{4i}, x_{5i}, x_{6i}, x_{7i}, y_i\} \quad (10)$$

The minimum number of input vector linearly independent forming the training set depends on the number of synaptic weights. Regarding the outputs, the ANN's only have one: the maximum value observed in the quakes occurred the next five days, in their corresponding cell. The activation function selected is the sigmoid. Mathematically this function is formulated as Eq. (11):

$$\Phi(Xi) = \frac{1}{1+e^{-Xi}} \quad \text{Where} \quad X_i = \phi\,(\textstyle\sum w_{ij}\, x_i) \quad (11)$$

And W_{ij} are the connection weights between unit i and unit j, and u_i are the signals arriving from unit i. The signal generated by unit i is sent to every node in the following layer or is registered as an output if the output layer is reached (Reyes et al. 2013). To access the performance of the ANN's design, several parameters have been used. In practical: 1. True positives (TP). The number of times that the ANN predicted an earthquake and an earthquake did occur during the next 5 days. 2. True negatives (TN). The number of times that the ANN did not predict an earthquake and no earthquake occurred. 3. False positives (FP). The number of times that ANN predicted an earthquake but no earthquake occurred during the next 5 days. 4. False negative (FN). The number of times that the ANN did not predict an earthquake but an earthquake did occur during the next 5 days. If the output does not exceed the should and the maximum observed magnitude M_s during the next five days is less than the threshold ($M_s < T_k$ in next 5 days), this situation is called zero – level hit, and denoted by P_0. On the other hand, if the output ≥ threshold and the maximum observed magnitude M_s during the next 5 days is larger than the threshold ($M_s \geq T_k$ in next 5 days), the situation is called one – level hit, and denoted by P_i. But probabilities widely used by seismologists to evaluate performance of approaches are calculated as follows Eqs. (12 and 13):

$$P_0 = \frac{\#(zero-level\ hits)}{N0} = \frac{TN}{TN+FN} \quad (12)$$

$$P_1 = \frac{\#(one-lvel\ hits)}{N1} = \frac{TP}{TP+FP} \quad (13)$$

Where N_0 = TN + FN denotes the time that the ANN predicted the zero – level and N_1 = TP + FP the time that the ANN predicted the one – level. Obviously, $N=N_0 + N_1$ denotes the total number of possible prediction. Additionally, two more parameters have been used to evaluate performance of the ANN's, as they correspond to common statistical measures of supervised classifiers performance. These two parameters sensitivity or rate of actual positives correctly identified as such (denoted by S_n) and specificity or rate of actual negatives correctly identified (denoted by S_p), are defined as (Eqs. 14 and 15):

$$S_n = \frac{TP}{TP+FN} \quad (14)$$

$$S_p = \frac{TN}{TN+FP} \quad (15)$$

CONCLUSIONS

Tables 2, 3, and 4 show training values and ANN's performance for three zones in Hormozgan Province. For Bandar Abbas zone, the training set contained the 105 linearly independent vectors occurred from May 20th 2002 to June 30th 2004. Analogously, the test set included the vectors generated from July 1st 2004 to August 20th 2005(Table 2). For Minab zone, the training set contained the 89 linearly independent vectors occurred from September 20th 1999 to November 30th 2003. Analogously, the test set included the vectors generated from December 1st 2003 to August 20th 2004(Table 3). For Hajabad zone, the training set contained the 115 linearly independent vectors occurred from April 20th 1997 to August 31th 2000. Analogously, the test set included the vectors generated from September 1st 2000 to August 20th 2001(Table 4). In this study the high values of P_0 and P_1 obtained for all the zones indicate that the input variables were, indeed, strongly correlated with the observed magnitude in a near future. The ANN's were capable of indirectly learning Omori/Utsu and Gutenberg-Richter's laws, confirming thus the great ability these techniques have in the seismology field (Reyes and Cardenas 2010). This fact confirms that the choice of such input vectors was adequate. With reference to the specificity, all the zones obtained values especially high. This fact is of the utmost significance, as it is extremely important not to active false alarm in seismology due to the social impact they may cause.

Table 2. Training values and ANN's performance for Bandar Abbas zone

Parameters	Value	ANN
TP	14	5
TN	69	24
FP	7	15
FN	29	7
P_0	70.4%	77.4%
P_1	66.6%	25.0%
S_n	32.5%	41.6%
S_p	14.5%	61.5%
Average	46.0%	51.4%

Table 3. Training values and ANN's performance for Minab zone

Parameters	Value	ANN
TP	15	18
TN	75	89
FP	6	4
FN	32	21
P0	70.0%	80.0%
P1	71.2%	82.0%
Sn	32.0%	46.2%
Sp	92.5%	95.7%
Average	66.5%	75.9%

Table 4. Training values and ANN's performance for Hajiabad zone

Parameters	Value	ANN
TP	11	19
TN	81	41
FP	4	6
FN	25	16
P0	76.4%	71.9%
P1	73.3%	76.0%
Sn	30.5%	54.2%
Sp	95.3%	87.2%
Average	68.8%	72.3

REFERENCES

Adeli H and Panakkat A (2009) A probabilistic neural network for earthquake magnitude prediction, Neural Networks 22, 1018-1024

Allen CR (1982) Responsibilities in earthquake prediction. Bulletin of the Seismological Society of America 662069-2074

Bath M (1965) Lateral inhomogeneities in the upper mantle, Tectonophysics 2 (483-514)

BHRS (Building and Housing Research Center, http://www.bhrc.ac.ir (2005), Iranian Code of Practice for Seismic Resistance Design of Buildings, Standard No. 2800, Third Edition.

Dimer de Oliveira F (2012) Can we trust earthquake cluster detection tests? Geophysical Research Letters 39, L17305

IIEES (2003) International Institute of Engineering and Seismology, Tehran, Iran, http://www.iiees.ac.ir

IRSC (2007) Iranian Seismological Center, Institute of Geophysics, University of Tehran, Iran, http://www.irsc.ut.ac.ir

Kalantari Khandani H, Ataei Daryaei G and Pourtorogh O (2001) Geography of Hormozgan province, Company of edition of text books of Iran, 84 pp

Kavei M (2008) Investigations on seismotectonics of parts of Hormozgan Province in southern Iran, Ph.D. Thesis, Pune University, Pune, India

Marzocchi W and Zechar JD (2011) Earthquake forecasting and earthquake prediction: different approaches for obtaining the best model, Seismological Research Letters 82(3):442-448

Nowroozi AA (1976) Seismotectonic provinces of Iran, Bulletin of the Seismological Society of America, Vol. 66, No. 4, 1249-1276

Nuannin P (2006) the potential of b-value variations as earthquake precursors for small and large events. Technical report 183. Uppsala University, Sweden

Okal EA, Romanovicz BA (1994) on the variation of b-value with earthquake size, physics of the Earth and Planetary Interiors 87: 55-76.]

Perez P and Reyes J (2006) an integrated neural network model for PM10 forecasting Atmospheric Environment 40: 2845-2851

Reyes J and Cardenas V (2010) A Chilean seismic regionalization through a Kohonen neural network, Neural Computing and Applications 19: 1081-1087

Utsu T (1961) A statistical study on the occurrence of aftershocks, Geophysical Magazine 30: 521-605