



HAL
open science

Estimating the Probability of Earthquake Magnitude Between $M_w = 4$ and $M_w = 5$ for Turkey

Türkay Dereli, Cihan Çetinkaya, Nazmiye Çelik

► **To cite this version:**

Türkay Dereli, Cihan Çetinkaya, Nazmiye Çelik. Estimating the Probability of Earthquake Magnitude Between $M_w = 4$ and $M_w = 5$ for Turkey. 2nd International Conference on Information Technology in Disaster Risk Reduction (ITDRR), Oct 2017, Sofia, Bulgaria. pp.96-107, 10.1007/978-3-030-18293-9_9 . hal-02280325

HAL Id: hal-02280325

<https://inria.hal.science/hal-02280325v1>

Submitted on 6 Sep 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

Estimating the Probability of Earthquake Magnitude between Mw=4 and Mw=5 for Turkey

Türkay Dereli^{1,2}, Cihan Çetinkaya¹, Nazmiye Çelik¹

¹ Gaziantep University, Industrial Engineering, 27310 Gaziantep, Turkey

² Iskenderun Technical University, 31200 Hatay, Turkey
dereli@gantep.edu.tr, cihancetinkaya@gantep.edu.tr,
nazmiye@gantep.edu.tr

Abstract. Earthquake is a type of disaster that occurs suddenly in different magnitudes. When magnitude of an earthquake increases it is expected that the effects are much more. Earthquakes in varying magnitude between 4Mw and 5Mw cause uneasiness among the public even if they do not cause heavy damage. The aim of this study is to estimate the probability of an earthquake between 4.0 and 5.0 by using artificial neural network model. Monthly real data between 2006 and 2015 is used for the model. Data is analyzed in MATLAB neural network tool, then estimated output value obtained via analysis and output of test value is compared with regression equation. Besides, seasonal effects on magnitude of earthquake are examined. Results show that 90.51 % of the earthquake probability between 4.0 and 5.0 can be estimated by using artificial neural network model.

Keywords: Artificial neural network, earthquake, magnitude, seasonal effect, MATLAB

1 Introduction

Earthquake is a sudden, rapid shaking of the Earth that causes losses in terms of human and materials also leaving psychological impact. Estimating the magnitude of the next earthquake, within a restricted area and time, appears as an almost impossible task [1]. Adeli and Panakkat [2] presented earthquake magnitude estimation between 4.5 and 6.0 using eight parameters including significant seismic events, mean square deviation etc. On the other hand, for this model studied interval for earthquake magnitudes is estimated between 4.0 and 5.0 because earthquake frequency in this interval is more than frequency of interval with $M_w > 5$ and effects are much more than the small magnitudes. The parameters used as independent variables in this study are the total number of earthquakes in various magnitudes. Magnitude between 4.0 and 5.0 for earthquake is unsettling among people and it creates a fear of a bigger earthquake because of average severity and high probability. Because of this unsettlement among people, probability of earthquake magnitude between 4.0 and 5.0 is chosen as dependent variable. Data is analyzed for Turkey because large part of Turkey is included in the earthquake zone because of the many small plates among the large plates. Contribution of this study

is by looking at the numbers of earthquakes in different magnitudes within a month, it can be estimated the probability of an earthquake in the specified magnitude interval.

The rest of the study is arranged in the following steps. Section 2 presents related works about the topic. Section 3 presents methodology of study with subsections: normalization of data, artificial neural network model and analyses, seasonal effects of earthquakes. Section 4 describes results of the study and finally, conclusion is summarized in the last section.

2 Literature Review

Artificial neural networks are computing systems based on interpretation of the process of biological neuron networks. Neural networks have been implemented in wide area such as transportation [3, 4], signal processing[5], medical[6,7] etc. Many scientists tried to implement Artificial Neural Networks (ANNs) to the issues related to earthquakes, getting attractive and encouraging results [8]. Alves [9] developed earthquake forecasting method integrating several tools in a neural network for financial analysis. This method was tested within different years with wide time and location perspective. Chattopadhyays [10] predicted the magnitude of earthquake over Indian subcontinent benefitting artificial neural network with backpropagation learning. ANN model established by Gul and Guneri [11] for the earthquake casualty estimation, which takes into account earthquake time, earthquake magnitude, and population frequency as the parameters for training network in Turkey from 1975. Murru et al. [12] proposed time-dependent and time-independent earthquake breakings for the Marmara Region in Turkey based on new fault segmentation model. Asencio-Cortes et al. [13] appraised correctness of artificial neural networks when used to estimate earthquakes magnitude in Tokyo. Azam et al.[14] classified earthquake patterns concerning identified characteristics using ANN based networks, and then either supervised or unsupervised techniques were used for estimation. Fawzy and Arslan [15] tried to estimate building reactions to big earthquakes benefitting actual data collected from surveys carried out after the real earthquakes. A neural network model was proposed to estimate the horizontal displacement of the ground in both ground slope and free face situations in order to liquefaction-induced lateral spreading by Baziar and Ghorbani [16]. Reyes et al.[17] presented a novel earthquake estimation system based on artificial neural networks for estimating earthquakes in Chile. Paper proposed by Alarifi et al. [18] demonstrated the implementation of artificial intelligent estimation model which used to estimate the magnitude of future earthquakes in northern Red Sea area including Sinai Peninsula, the Gulf of Aqaba, and the Gulf of Suez. In section 3, the approaches in this study are discussed. Li and Liu [19] presented a different approach of combining particle swarm algorithm and back propagation neural network to estimate earthquake magnitude. Their model gave better results and faster convergence rate. Radial basis function network and adaptive neuro fuzzy inference system were applied to predict earthquake occurrences in Iran considering spatial-temporal variations [20]. LM-BP algorithm was implemented by Zhou and Zhu [21] to the earthquake prediction considering fast ve-

locity and the strong fault tolerant. Moustra et al. [22] evaluated artificial neural network performance using time series magnitude data and seismic electric signals to estimate earthquakes. The results were relatively accurately. A Time series was also used by Lakshimi and Tiwari [23] making a comparative analyses including non-linear forecasting model and artificial neural network. Results acquired by two methods were consistent and in good accord. Seismic indicators have been also widely used in neural network to predict earthquakes [24, 25, 26].

Neural networks have been implemented successfully to deal with complex problems with different tools to estimate earthquakes.

3 Methodologies

Earthquake is a disaster type that takes place almost every day and the impact of a strong earthquake is disruptive. Technically, the earthquake is a phenomenon of vibrations that suddenly emerge in waves due to breaks in the earth's crust, and thus shake the earth. Magnitude is too significant in terms of earthquake effects. Magnitude is a measure of the energy generated during an earthquake. In this study, earthquakes with magnitude between 4.0 and 5.0 have been analyzed using artificial neural network model with subsections: normalization of data, artificial neural network model and analyses, seasonal effects of earthquakes. Components of model and model design have been examined in detail. The model is formed by using MATLAB neural network tool.

Artificial neural networks are computing systems based on interpretation of the biological neuron networks process. These models bring solution to real world problems which interrelate between a set of given input patterns and set of known target output [27]. Structure of a classic neural network model is shown in figure 1.

Properties of neural networks are nonlinearity, input-output association (mapping), adaptability, evidence-based response, contextual information, analysis and design standard, neurobiological metaphor, applicability to large-scale technology and fault tolerance [28]. These systems are based on gaining the ability to learn by manipulating inputs over time. Many nerve cells have parallel learning capacity in one piece, and this is probably the most important aspect [29].

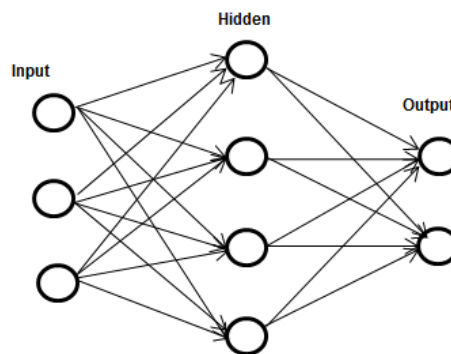


Fig. 1. Test and estimated output values

The steps to be taken in the next stages of the study are as follows; normalization process is applied to provide data consistency. After the normalization of the data is completed, artificial neural network model is conducted. Test and training sets and the most appropriate activation function is determined. After the network type is determined, the number of layers and the number of neurons in hidden layers are determined. For the simulation process, weights are obtained by via training parameters and they are available to obtain the desired output. After all a new neural network model is created.

3.1 Normalization of data and determining output value

Data is normalized to increase accuracy of data. The following formula in equation 1 is used for normalization [30]. In the model log-sis function is used as transfer function because it is a continuous derivable function and network type is chosen as feed-forward backprop.

$$Mr=0.8*[(Mr-Mmin)/(Mmax-Mmin)]+0.1 \quad (1)$$

Mr=Real observed data
Mmin=Minimum of data
Mmax=Maximum of data

In appendix 1, all data is shown before the normalization process insert in a table. The last column shows output values. These output values are computed according to statistical analyses and linguistic variables.

Firstly, probabilities of earthquake occurrence between Mw=4 and Mw=5 are statistically analyzed and following results are obtained.

Data Summary;
Number of Data Points = 120
Min Data Value = 0.0043
Max Data Value = 0.0482
Sample Mean = 0.0171
Sample Std Dev = 0.00935

Accordingly, these probabilities are expressed as linguistic expressions. In table 1, linguistic expressions and then their digitized states are shown.

Table 1. Converting linguistic expressions to numbers

	Very low	Low	Medium	High
Formulation	$\leq(\text{sample mean}-\text{std dev})$	$\leq(\text{sample mean}), >(\text{sample mean}-\text{std dev})$	$\leq(\text{sample mean}+\text{std dev}), >(\text{sample mean})$	$>(\text{sample mean}+\text{std dev})$
Digitization	1	2	3	4

Linguistic expressions are normalized after being digitized and used as output values.

3.2 Artificial neural network model and analysis

After all, above mentioned processes, model is formed by using MATLAB neural network tool. The following steps have been implemented:

- While 84 samples (months) are used for training set, 36 samples (months) are used for test set.
- Number of epochs is chosen 1000 and max-fail is estimated as 6.
- After training network, weights are obtained and used for computing output value when input values are given. Weights are shown in table 2. MATLAB code which is written in respect to weights is shown in appendix 2 for computing output values [30]. In MATLAB code, E is the normalized output value. The actual output value is obtained by applying the inverse of the normalization process. Accordingly, network is simulated using test input values, and then test output values and estimated output values are compared as shown figure 2.

Table 2. Weight of layers

Iw{1,1}-Weight to layer 1	Iw{2,1}-Weight to layer	b{1}-Bias to layer 1	b{2}-Bias to layer 2
[-2.4199 1.667 - 3.7098 -0.071999; - 0.45022 0.99641 - 2.7364 3.5565; 3.9526 -1.1322 -1.3897 1.8254; -0.0059579 4.1033 0.98436 2.1465; -1.1492 - 3.5649 -1.5197 2.7367; -2.7365 2.258 4.2554 0.15928; 0.088907 1.7687 3.3905 1.0296; 1.202 2.9674 1.564 -3.0521]	[-1.5627 0.66908 -0.40774 0.87236 0.90156 3.7318 -3.169 1.4499]	[4.6993; 3.6089; 2.0318; -0.14941; 0.20621; -1.1002 - 4.7703; 4.754]	[-1.1608]

- 2 layers and 8 neurons are used for this model. 3 years data is constituted test earthquake counts [31].

Estimated data and real data have similar characteristics. According to the regression analysis done in excel, value of R2 is equal to 0.9051. This result shows that 90.51 % of the variability in the magnitude of earthquake between 4Mw and 5Mw can be estimated with using artificial neural network model.

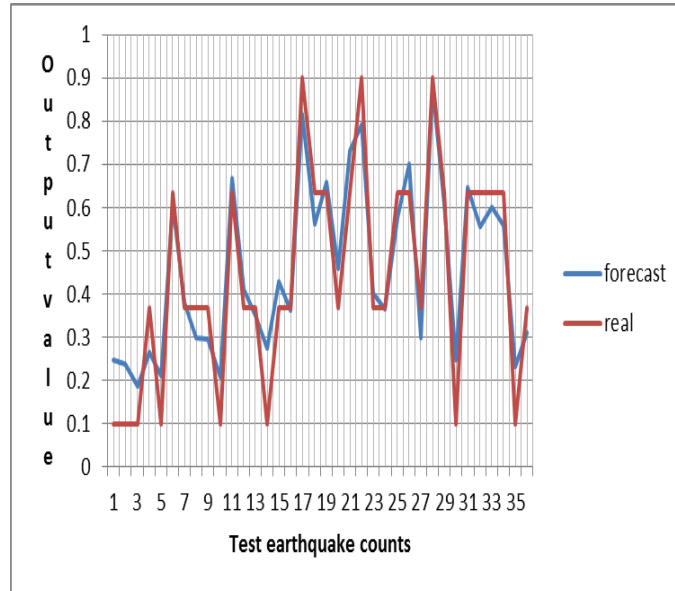


Fig. 2. Test and estimated output values

3.3 Seasonal effects of earthquakes

When seasonal effects of earthquake are considered, it is observed that the frequency increases especially in spring and autumn as in the figure 3. There are relatively few earthquakes in winter months compared to summer months.

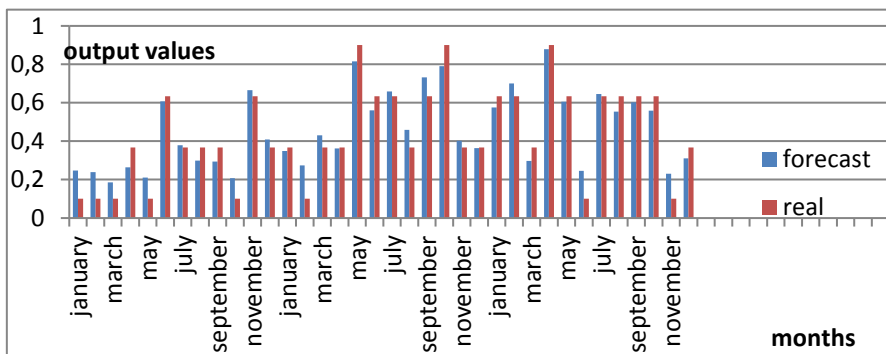


Fig. 3. Earthquake seasonal results

4 Results

First 86 data (first 86 months) is selected as training set and last 36 data is selected as test set before data entry to the system. 2 layers and 8 neurons are used and log-sis function is benefitted as transfer function. Network type is chosen as feed-forward backprop. After training system, regression plots are handled as seen figure 4. Regression plots display the outputs of networks in connection with targets for training, validation, and test sets.

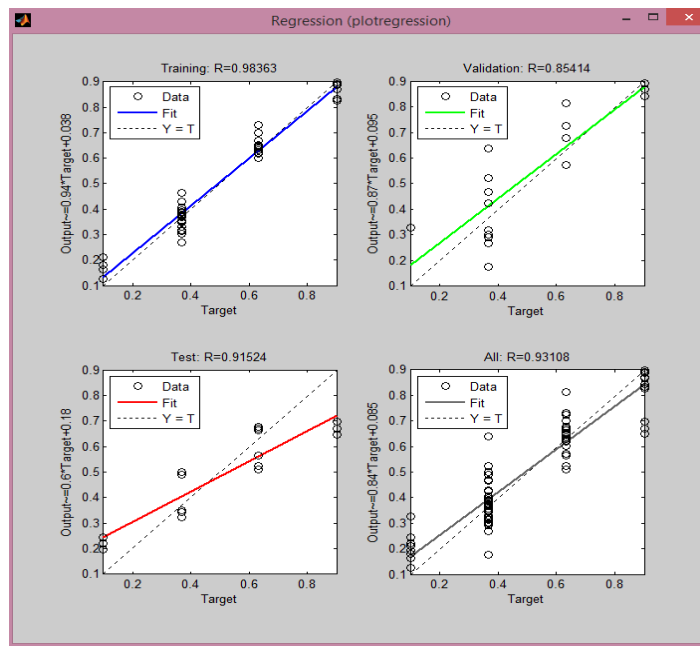


Fig. 4. Regression in neural network

For this problem, R value for training set is above 0.93 [32] so fit is good for this data set. For test set, R value is 0.91 that is below 0.93 but comparatively the fit can be said well. For validation set, R value is equal to 0.85 is below 0.93. For more accurate results the sets could be retrained. But for all results, R value is equal to 0.93 and these results are accurate.

As seen in figure 5, best validation performance has occurred at epoch 0 and is equal to 0.0042663.

Accordingly, the test set error and the validation set error has same features. So, the results are logical in the light of these characteristics. In table 3, test output values and estimated output values are shown.

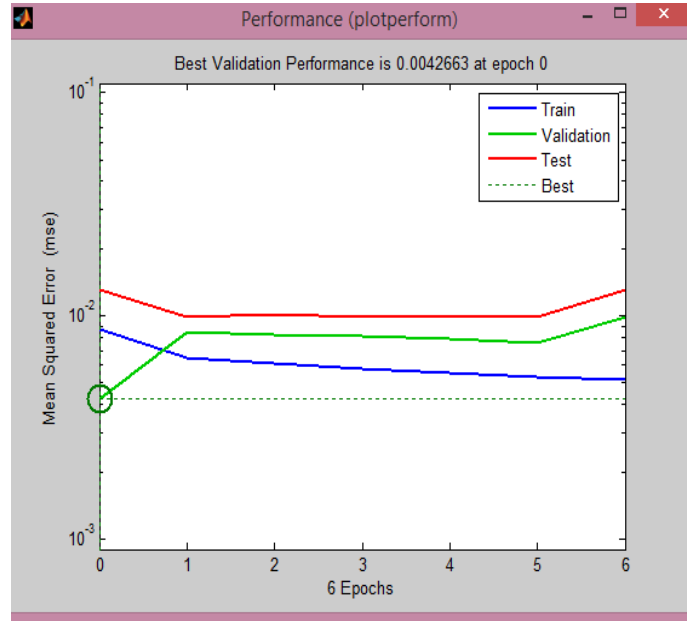


Fig. 5. Best validation performance

Table 3. Comparison of test output values and estimated output values

	Jan.	Feb.	March	April	May	June	July	Au- gust	Sept.	Oct.	Nov.	Dec.
Real	0.1	0.1	0.1	0.37	0.1	0.633	0.37	0.37	0.37	0.1	0.633	0.37
Forecast	0.247	0.238	0.185	0.26	0.21	0.607	0.38	0.298	0.29	0.20	0.67	0.41
Real	0.37	0.1	0.37	0.37	0.9	0.63	0.63	0.37	0.63	0.9	0.37	0.37
Forecast	0.34	0.27	0.43	0.36	0.81	0.56	0.65	0.459	0.73	0.79	0.40	0.36
Real	0.63	0.63	0.37	0.9	0.63	0.1	0.63	0.63	0.63	0.63	0.1	0.37
Forecast	0.576	0.70	0.297	0.87	0.60	0.24	0.64	0.55	0.60	0.56	0.231	0.31

Except that, the new output values can be obtained with the randomly selected input values. MATLAB code in appendix 1 shows output value calculations.

5 Conclusion

Earthquakes can cause many tangible or intangible losses. Uneasiness can be an example for intangible losses. Actually, earthquakes in varying magnitude between 4Mw and 5Mw cause uneasiness among the public even if they do not cause heavy damage. In this study, artificial neural network model is implemented for estimating probability of future earthquakes magnitudes between 4.0 and 5.0. Artificial neural networks have capabilities to analyze and tackle with complicated relations to estimate earthquake

magnitudes. Proposed model has used four magnitude intervals as independent variables. Probability of earthquake occurrence in varying magnitude is used as dependent variable. Monthly real data between 2006 and 2015 for Turkey has been used for analyses. Results show that model can display estimation of magnitudes between special intervals accurately. Furthermore, 90.51 % of the variability in the magnitude of earthquake between 4Mw and 5Mw can be estimated with using artificial neural network model. Besides, when seasonal effects of earthquake are considered, it is observed that the frequency increases especially in spring and autumn. In addition to determining the probability of an earthquake for different magnitudes, magnitude of earthquake can be estimated by different parameters using this model. Thanks to this study, the number of earthquakes in the range of $M_w=4.0$ to $M_w=5.0$ in a season can be estimated for next years.

References

1. Florido, E., Aznarte, J., Morales-Esteban, A., Martínez-Álvarez, F.: Earthquake Magnitude Prediction Based on Artificial Neural Networks: A Survey. *Croatian Operational Research Review*. 159--169 (2016)
2. Adeli, H., Panakkat, A.: A Probabilistic Neural Network for Earthquake Magnitude Prediction. *Neural Networks*. 22, 1018--1024(2009)
3. Stathopoulos, A., Dimitriou, L., Tsekeris, T.: Fuzzy Modeling Approach for Combined Forecasting of Urban Traffic Flow. *Computer-Aided Civil and Infrastructure Engineering*, 23,521--535(2008)
4. Vlahogianni, E. I., Karlaftis, M. G., Golias, J. C.: Temporal Evolution of Short Term Urban Traffic Flow: A Non-Linear Dynamics Approach. *Computer-Aided Civil and Infrastructure Engineering*, 23, 536--548(2008)
5. Cichocki, A., Zdunek, R.: Multilayer Nonnegative Matrix Factorization using Projected Gradient Approaches. *International Journal of Neural Systems*, 17, 431--446(2007)
6. Kuo, H. J., Chiu, H. W., Lee, C. N., Chen, T. T., Chang, C. C., Bien, M. Y.: Improvement in the Prediction of Ventilator Weaning Outcomes by an Artificial Neural Network in a Medical ICU. *Respiratory Care*, 60, 1560--1569(2015)
7. Andrei, C. L., Oancea, B., Nedelcu, M., Sinescu, R.D.: Predicting Cardiovascular Diseases Prevalence using Neural Networks. *Economic Computation and Economic Cybernetics Studies and Research*, 49, 73--84(2015)
8. Buscema, P.M, Massini, B.G., Maurelli, G.: Artificial Adaptive Systems to Predict the Magnitude of Earthquakes. *Bollettino di Geofisica Teorica ed Applicata*. 56, 227--256(2015)
9. Alves, E. I.: Earthquake Forecasting using Neural Networks: Results and Future Work. *Nonlinear Dynamics*, 44, 341--349(2006)
10. Chattopadhyay, G., Chattopadhyay, S.: Dealing with the Complexity of Earthquake Using Neurocomputing Techniques and Estimating its Magnitude with Some Low Correlated Predictors. *Arab J Geosci*. 247--255(2009)
11. Gul, M., Guneri, A. F.: An Artificial Neural Network-Based Earthquake Casualty Estimation Model for Istanbul City. *Nat Hazards*. 84, 2163--2178(2016)
12. Murru, M., Akinci, A., Falcone, G., Pucci, S., Console, R., Parsons, T.: $M \geq 7$ Earthquake Rupture Forecast and Time-Dependent Probability for the Sea of Marmara Region, Turkey. *Journal of Geophysical Research: Solid Earth*. 2679--2707(2016)

13. Asencio-Cortes, G., Martı́nez-Alvarez, F., Troncoso, A., Morales-Esteban, A.: Medium–Large Earthquake Magnitude Prediction in Tokyo with Artificial Neural Networks. *Neural Comput & Applic.* 28, 1043--1055(2017)
14. Azam, F., Sharif, M., Yasmin, M., Mohsin, S.: Artificial Intelligence Based Techniques for Earthquake Prediction: A Review. *Sci.Int.(Lahore)*. 26, 1495--1502(2014)
15. Fawzy, D., Arslan, G.: Development of Building Damage Functions for Big Earthquakes in Turkey. *Procedia - Social and Behavioral Sciences*. 195, 2290--2297(2015)
16. Baziar, M., Ghorbani, A.: Evaluation of Lateral Spreading Using Artificial Neural Networks. *Soil Dynamics and Earthquake Engineering*. 25, 1--9(2005)
17. Reyes, J., Morales-Esteban, A., Martı́nez-Álvarez, F.: Neural Networks to Predict Earthquakes in Chile. *Applied Soft Computing*. 13, 1314--1328(2012)
18. Alarifi, A.S.N., Alarifi, N.S.N., Al-Humidan, S.: Earthquakes Magnitude Prediction Using Artificial Neural Network in Northern Red Sea Area. *Journal of King Saud University*. 24, 301--313(2012)
19. Li, C. and Liu, X.: An Improved PSO-BP Neural Network and Its Application to Earthquake Prediction. In *Proceedings of the Chinese Control and Decision Conference*. pp. 3434--3438(2016)
20. Zamani, A., Sorbi, M. R. and Safavi, A. A.: Application of Neural Network and ANFIS Model for Earthquake Occurrence in Iran. *Earth Science Informatics*. 6, 71--85(2013)
21. Zhou, F. and Zhu, X.: Earthquake Prediction Based on LM-BP Neural Network. *Lecture Notes in Electrical Engineering*. 270, 13--20(2014)
22. Moustra, M., Avraamides, M. and Christodoulou, C.: Artificial Neural Networks for Earthquake Prediction using Time Series Magnitude Data or Seismic Electric Signals. *Expert Systems with Applications*. 38, 15032--15039(2011)
23. Srilakshmi, S., Tiwari, R.K.: Model Dissection from Earthquake Time Series: A Comparative Analysis using Nonlinear Forecasting and Artificial Neural Network Approach. *Computers and Geosciences*. 35, 191--204(2009)
24. Asencio-Corte's, G., Martı́nez-A´lvarez, F., Morales-Esteban, A., Reyes, J., Troncoso, A.: Improving Earthquake Prediction with Principal Component Analysis: Application to Chile. *Lect Notes Artif Intell*. 9121, 393--404(2015)
25. Martı́nez-A´lvarez, F., Reyes, J., Morales-Esteban, A., Rubio-Escudero, C.: Determining the Best Set of Seismicity Indicators to Predict Earthquakes. Two Case Studies: Chile and the Iberian Peninsula. *Knowledge Based System*. 50,198--210(2013)
26. Panakkat A, Adeli H.: Neural Network Models for Earthquake Magnitude Prediction using Multiple Seismicity Indicators. *Int J Neural Syst*. 17,13--33(2007)
27. Rafiq MY, Bugmann G, Easterbrook DJ.: Neural Network Design for Engineering Applications. *Computers and Structures*. 1541--1552(2001).
28. Haykin, S.: *Neural Networks and Learning Machines*, Pearson Education, Inc., Upper Saddle River, New Jersey 07458.(2009)
29. Kriesel, D.: *A Brief Introduction to Neural Networks (ZETA2-EN)*. (2005).
30. Uguz, S. :Yapay Sinir Ağları-Matlab Uygulaması.
31. https://ybssoftware.files.wordpress.com/2011/03/ysa_uygulama.pdf
32. RETMC.: Bogazici University Kandilli Observatory And Earthquake Research Institute Regional Earthquake-Tsunami Monitoring Center,
33. <http://www.koeri.boun.edu.tr/sismo/2/deprem-verileri/yillik-deprem-haritalari/>, last accessed 2017/06/21.
34. MathWorks.:Fit Data with a Neural Network, <https://www.mathworks.com/help/nnet/gs/fit-data-with-a-neural-network.html>, last accessed 2017/06/21.

Appendix 1
(Numbers of earthquakes in different magnitudes between 2006 and 2015)

No	Season	Mb>=2-Mb<=2.9	Mb>=3-Mb<=3.9	Mb>=4-Mb<=5	Mb>=5-Mb<=6	Pro.	No	Season	Mb>=2-Mb<=2.9	Mb>=3-Mb<=3.9	Mb>=4-Mb<=5	Mb>=5-Mb<=6	Pro.
1	january	155	170	9	0	4	61	january	657	122	8	1	2
2	february	167	129	12	1	4	62	february	661	199	15	1	3
3	march	187	161	9	0	3	63	march	761	186	10	0	2
4	april	254	202	11	0	3	64	april	727	154	17	0	3
5	may	313	167	8	0	2	65	may	2094	440	24	3	2
6	june	245	198	6	1	2	66	june	1172	261	16	1	2
7	july	251	142	15	0	4	67	july	1048	134	12	1	2
8	august	246	125	6	2	2	68	august	826	142	14	0	2
9	september	202	134	9	0	4	69	septembe	1010	186	15	3	2
10	october	249	172	11	2	3	70	october	1563	774	100	9	4
11	november	192	106	7	0	3	71	novembe	2292	534	62	6	3
12	december	206	162	11	1	4	72	december	1545	208	24	0	2
13	january	163	249	9	1	3	73	january	1295	270	25	2	2
14	february	274	232	10	3	3	74	february	1089	166	11	1	2
15	march	254	271	18	0	4	75	march	1303	182	15	2	2
16	april	219	219	13	1	4	76	april	1576	239	19	0	2
17	may	269	202	7	0	2	77	may	1919	223	22	3	2
18	june	245	191	6	0	2	78	june	1934	181	27	3	2
19	july	254	147	8	0	3	79	july	1447	99	10	2	1
20	august	228	185	11	2	4	80	august	1400	107	7	1	1
21	september	242	157	12	1	4	81	septembe	1439	119	14	2	2
22	october	252	183	21	1	4	82	october	1377	109	9	0	1
23	november	213	236	13	3	4	83	novembe	2289	167	15	0	1
24	december	397	393	17	2	3	84	december	1332	141	10	3	1
25	january	422	339	19	0	3	85	january	1601	213	12	2	1
26	february	289	212	5	1	2	86	february	1299	100	10	0	1
27	march	321	230	12	2	3	87	march	1364	101	9	3	1
28	april	607	330	11	1	2	88	april	1480	123	13	1	2
29	may	399	256	8	0	2	89	may	1659	110	10	1	1
30	june	418	218	16	1	3	90	june	1213	110	25	1	3
31	july	347	244	15	1	3	91	july	1098	116	15	1	2
32	august	386	214	11	2	3	92	august	1136	90	12	1	2
33	september	389	166	13	0	3	93	septembe	1123	120	13	3	2
34	october	474	191	25	2	4	94	october	977	124	5	0	1
35	november	472	186	17	0	3	95	novembe	886	102	20	2	3
36	december	618	238	8	2	2	96	december	895	99	13	1	2
37	january	502	196	11	1	2	97	january	618	85	7	0	2
38	february	491	204	6	1	2	98	february	599	61	4	0	1
39	march	709	218	5	0	1	99	march	659	94	10	0	2
40	april	561	180	11	0	2	100	april	606	96	8	2	2
41	may	730	261	9	0	2	101	may	937	199	34	1	4
42	june	677	268	16	3	2	102	june	687	108	14	2	3
43	july	476	210	28	1	4	103	july	686	110	17	0	3
44	august	473	161	14	0	3	104	august	805	114	14	3	2
45	september	474	173	22	1	4	105	septembe	631	93	17	1	3
46	october	446	170	6	1	2	106	october	531	75	17	0	4
47	november	362	177	12	0	3	107	novembe	661	121	10	2	2
48	december	349	157	7	2	2	108	december	740	108	10	2	2
49	january	492	196	10	0	2	109	january	633	96	13	1	3
50	february	569	209	9	1	2	110	february	535	78	14	0	3
51	march	949	352	24	4	3	111	march	628	108	6	1	2
52	april	826	155	8	1	2	112	april	580	162	28	3	4
53	may	951	206	8	0	1	113	may	633	122	15	0	3
54	june	678	148	9	0	2	114	june	671	126	5	2	1
55	july	779	138	8	0	2	115	july	736	111	17	1	3
56	august	823	144	10	0	2	116	august	548	90	11	0	3
57	september	583	145	16	0	3	117	septembe	641	95	14	0	3
58	october	708	142	10	1	2	118	october	626	111	13	2	3
59	november	992	212	7	2	1	119	novembe	606	90	3	1	1
60	december	662	131	13	0	2	120	december	868	87	10	2	2

Appendix 2

```

%%input data
N1=input('enter a value');
N2=input('enter a value');
N3=input('enter a value');
N4=input('enter a value');

%% Normalization
A=0.8*( (N1-155) / (2292-150) )+0.1;
B=0.8*( (N2-61) / (774-61) )+0.1;
C=0.8*( (N3-3) / (100-3) )+0.1;
D=0.8*( (N4-0) / (9-0) )+0.1;

%%Formulation of forecast
E1=A*(-2.4149)+B*1.667+C*(-3.7098)+D*(-0.071999)+(4.6993);
E2=A*(-0.45022)+B*(-0.99641)+C*(-2.7364)+D*(3.5565)+(3.6089);
E3=A*(3.9526)+B*(-1.1322)+C*(-1.3897)+D*1.8254+(-2.0318);
E4=A*(-0.0059579)+B*(4.1033)+C*(0.98436)+D*(2.1465)+(-0.14941);
E5=A*(-1.1492)+B*(-3.5649)+C*(-1.5197)+D*(2.7367)+(0.20621);
E6=A*(-2.7365)+B*(2.258)+C*(4.2554)+D*(0.15928)+(-1.1002);
E7=A*(-0.088907)+B*(1.7687)+C*(-3.3905)+D*(1.0296)+(-4.7703);
E8=A*1.202+B*(2.9674)+C*(1.564)+D*(-3.0521)+(4.754);
F1=1/(1+exp(-E1));
F2=1/(1+exp(-E2));
F3=1/(1+exp(-E3));
F4=1/(1+exp(-E4));
F5=1/(1+exp(-E5));
F6=1/(1+exp(-E6));
F7=1/(1+exp(-E7));
F8=1/(1+exp(-E8));
E9=F1*(-1.5627)+F2*(0.66908)+F3*(-0.40774)+F4*(0.87236)+F5*(0.90156)+F6*(3.7318)+F7*(-3.169)+F8*(1.4499)+(-1.1608);
F9=1/(1+exp(-E9));
Emin=min([E1 E2 E3 E4 E5 E6 E7 E8]);
Emax=max([E1 E2 E3 E4 E5 E6 E7 E8]);
E=( (F9-0.1) / 0.8 ) * (Emax-Emin) + Emin;

```