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PERFORMANCE INVESTIGATION OF NEURO-FUZZY SYSTEM FOR EARTHQUAKE PREDICTION

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ABSTRACT

In this paper, the ability of Adaptive Neuro-Fuzzy Inference System (ANFIS) for the seismic moment prediction of the next earthquake has been investigated. To do so, two seismic indicators were used as inputs which were computed from the data related to the earthquakes recorded during last 63 years in a region which is located in southern Iran with 1° N latitude and 4° E longitude. The first indicator is the logarithm of the mean annual rate of exceedance for each record which is determined based on definition of Gutenberg-Richter law and the second indicator is time duration from the specified time origin. The output indicator is the logarithm of cumulative amount of seismic moment between the origin event and the future earthquake of each event. The test results with correlation factor 98% showed that ANFIS can be a useful tool for earthquake prediction.

Keywords: Earthquake; moment magnitude; Gutenberg-Richter law; neuro-fuzzy system; ANFIS; magnitude prediction.

1. INTRODUCTION

Developments concerning computational intelligence made in recent years have attracted engineers' attention toward one of the most challenging issues i.e. predicting earthquakes. Certain complexities and dynamics of earthquake have made researchers to use soft computing which means extracting data through numerical computations instead of common classic mathematics.

Neural network and fuzzy systems are both very popular techniques in soft computing.

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They includes approaches to human reasoning that try to make use of the human tolerance for incompleteness, uncertainly, imprecision and fuzziness in decision making processes [1]. Although the ability of neural networks [2-18] to predict some of seismic parameters have been investigated by researchers but there is a drawback with this method. The solution that a network has learned cannot be expressed. This problem is not with fuzzy systems. These systems are built from explicit knowledge which is expressed in fuzzy rules. There are several research based on fuzzy systems for earthquake prediction [19, 20]. However, it is sometimes difficult suitably to specify all the parameters of a fuzzy system. The combination of neural networks and fuzzy systems can help to enhance the performance of the system [21]. In a neuro-fuzzy system, the neural network learning algorithms are used to determine parameters of fuzzy system.

Earthquake forecasting is one of the challenging problems all over the world and predicting of the future earthquake in Iran which is one of the most seismically active countries is an open issue. In this paper, it is endeavored to study one of the strongest neuro-fuzzy systems which is called adaptive neuro-fuzzy inference system (ANFIS) with purpose of the future earthquake magnitude prediction in Iran.

2. EARTHQUAKE DATASET

Seismic data recorded in Iran are archived by the International Institute of Earthquake Engineering and Seismology (IIEES) and are available for free download at www.iiees.ac.ir. For this study, a region in Iran with the longitude 53 to 57 and latitude 27 to 28 has been selected and information of earthquakes which were included 1480 records between 1950 and 2013 has been collected.

The earthquake catalogue (IIEES) used in this study reports earthquake magnitudes in different scales. For Iranian plateau, Shahvar and et al.[22] presented relationships for converting earthquake magnitude scales to each other's. In local magnitude scale (ML) there is no considered difference between different wave types. Surface waves magnitude scale (Ms) and body waves magnitude scale (mb) are relate to a particular wave and each of Ms, mb, and ML is saturated in a particular level. Moment magnitude scale (Mw) is the only magnitude scale which is not saturated [23]. Therefore, the moment magnate is most suitable for creating a uniform seismic catalogue [23-27] and in this study, the magnitude scales of *mb*, *Ms* and *ML* were converted to *Mw* by equations 1 to 4 which are presented in [22] except the records whose Mw was reported:

$$Mw = 1.03\, mb - 0.057 \tag{1}$$

$$Mw = 0.701\, ML + 1.656 \tag{2}$$

$$Mw = 0.949\, Ms + 0.243 \quad for \quad Ms \geq 6.1 \tag{3}$$

$$Mw = 0.611\, Ms + 2.314 \quad for \quad Ms < 6.1 \tag{4}$$

Mw: moment magnitude scale.
mb: body waves magnitude scale.
Ms: surface waves magnitude scale.
ML: local magnitude scale.

3. ANFIS

Adaptive Neuro-Fuzzy Inference System (ANFIS) which is introduced by Jang [28], is one of the first hybrid neuro-fuzzy systems for estimating a function. ANFIS presented a Sugeno-type fuzzy system a special five-layer network. Fig. 1 shows structure of ANFIS for two inputs *x* and y with two rules and two membership functions.

ANFIS has five layers with following functions [27]:

First layer: parameters of membership function are kept in layer 1. In Fig. 1, A_1 and A_2 are membership functions for *x* and also B_1 and B_2 are membership functions for *y*.

Second layer: inputs of each node in layer 2 are membership degrees of each rule. In fact, every node in this layer is a circle node labeled *Π* which multiples the incoming signals and sends the product out.

Third layer: in this layer, the fulfillment degree of each rule is determined. Every node in this layer is a circle node labeled *N*. The *i*th node calculates the ratio of the *i*th rule's firing strength to the sum of all rules' firing strengths.

Fourth layer: the output of this layer has parameters that will be referred to as consequent parameters that are adjustable.

Fifth layer: final output of *f* is computed based on the all outputs of layers 1 to 4 and the single node in layer 5 is a circle node (adaptive node) labeled ∑ that computes the overall output as the summation of all incoming signals in this layer.

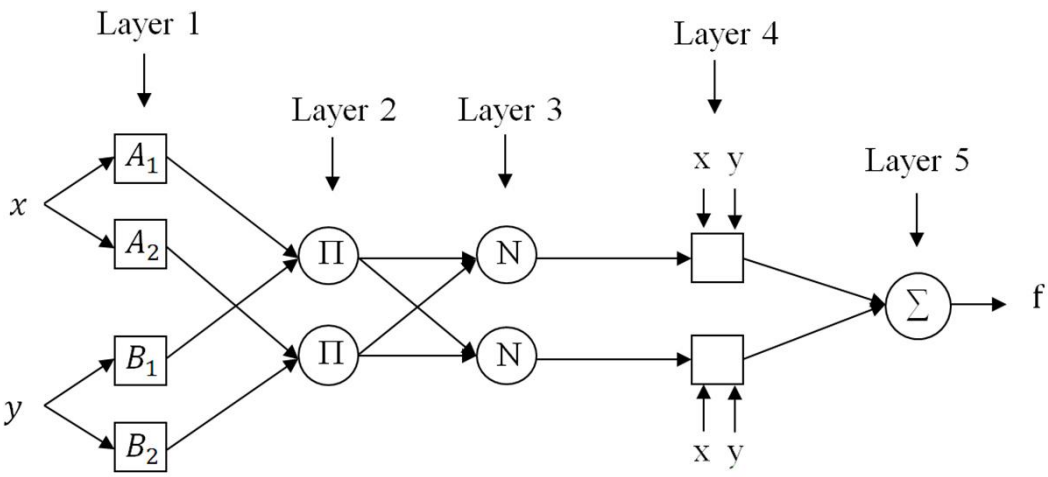

Figure 1. Structure of ANFIS with 2 inputs and 2 rules. A square node (adaptive node) has parameters while a circle node (fixed node) has none [28]

For ANFIS a mixture of back propagation (gradient descent) and Least Squares Estimate (LSE) is used. Back propagation is used to learn the antecedent parameters, i.e. the membership function, and LSE is to determine the coefficient of the linear combinations in the rules' consequents. A step in the learning procedure has two parts. In the first part the input patterns are propagated, and the optimal consequent parameters are estimated by an iterative least mean squares procedure, while the antecedent parameters are assumed to be fixed for the current cycle through the training set. In the second part the patterns are propagated again, and

in this epoch back propagation is used to modify the antecedent parameters, while the consequent parameters remain fixed. This procedure is then iterated [1].

4. DETERMINE THE INPUT VARIABLES OF ANFIS

4.1 Logarithm of mean annual rate of exceedance (LLm)

According to general definition of Gutenberg-Richter Rule, number of records for each magnitude in the specified region during last 60 years was determined in the specified region and relationships between logarithmic changes of annual number of incidents and magnitudes was studied (table 1). In this table, *s* is concerned with error of difference between amounts and regression line and R^2 is correlation factor.

Table 1: Relationship between logarithmic changes of annual number of incidents and magnitude

Equation number	Equation of regression	R^2	s
5	Log (Lm) = 2.843 – 0.6595 Mw	0.797	0.14
6	Log (Lm) = -3.969 + 2.185 Mw – 0.2867 Mw^2	0.914	0.21
7	Log (Lm) = -27.92 + 17.19 Mw – 3.348 Mw^2 + 0.2036 Mw^3	0.962	0.32

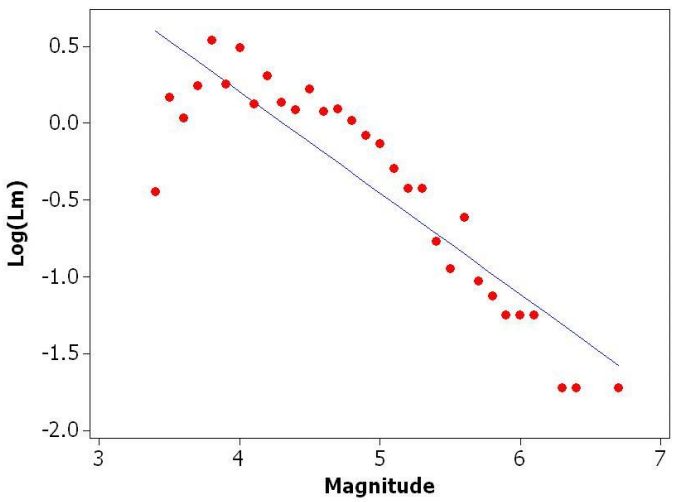

Figure 2. Scatter plot and line of regression (eq.5) between logarithm of mean annual of excedance (LLm) and Mw

According to table 1, Equations (6) and (7) are *more exact than the* Equation (5). Considering the manner of distribution of points (Figs. 2 to 4) it is clear that linear equation is less capable than other equations and also eq.7 has better results than eq.6. Therefore, logarithm of mean annual of excedance (LLm) for each magnitude was computed for all 1480 records of the selected region using eq.7. LLm was used as one of the inputs of ANFIS.

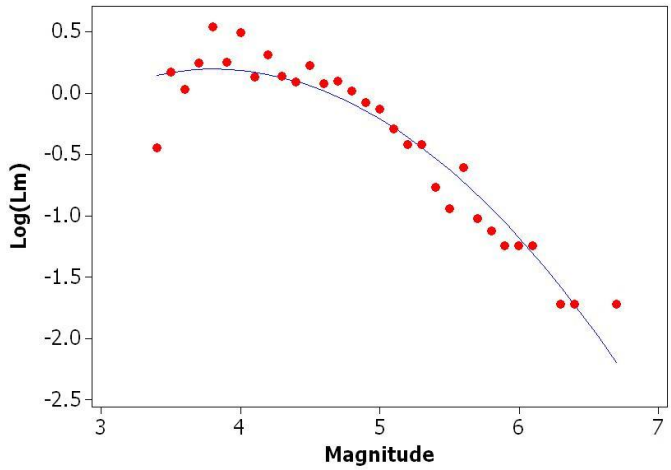

Figure 3. Scatter plot and curve of regression (Eq. (6)) between logarithm of mean annual of excedance (LLm) and Mw

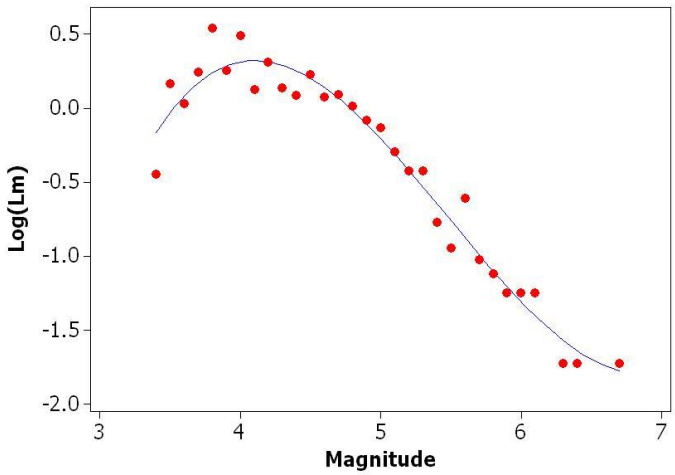

Figure 4. Scatter plot and curve of regression (Eq.(7)) between logarithm of mean annual of excedance (LLm) and Mw

4.2. Interval between each record from the origin time (TO)

The selection of the input variables is very important aspect for artificial intelligence modeling. This depends on the better understanding of the problem. Earthquake is a phenomenon which occurs over time. After reviewing several primary models to determine proper inputs for ANFIS, it was recognized that if time parameter in relation to a specified time is computed cumulatively, much better results will be obtained. The first record used as an origin time and therefore, intervals between all studied earthquakes and the time of origin were determined (TO) and used as the second input in the model. It is noted that time for event which is occurred after the last record is not clear and therefore, TO cannot calculate for the last record. Finally, there are 1479 records to create ANFIS.

5. DETERMINE THE OUTPUT VARIABLE OF ANFIS

5.1 Logarithm of cumulative seismic moment between the origin time and the next earthquake of each event (LMCN)

To calculate the output, first, the logarithm of seismic moment of each record was determined by eq.8 [23]. Then, the cumulative amount of seismic moment between the first record (occurred in the origin time) in the dataset and the next earthquake of each event was determined and used as an output of the model.

$$LM0 = 1.5\ Mw + 16.1 \tag{8}$$

Mw: moment magnitude scale.
LM0: logarithm of seismic moment.

6. ANFIS MODEL FOR EARTHQUAKE PREDICTION

1479 available data were divided into three equal parts considering their order. 493 data were taken for training of the model which was related to the records of the year 1950 to 10/12/1997. Also, to check the model, 493 data related to the records between 10/12/1997 and 09/14/2006 were taken; and to test the model, 493 data were taken which included the earthquakes happened between 09/14/2006 and 08/09/2013.

In the preparation data process, the amount of data was normalized. This action increases the speed and accuracy of the system in training. In this study, before the training of the model both input and output variables were normalized within the range 0.1 – 0.9 as follows:

$$X_i = 0.8\ \frac{x - x_{min}}{x_{max} - x_{min}} + 0.1 \tag{8}$$

x_i: is the normalized value of a certain parameter.
x: the measured value for the parameter.
x_{min} : minimum values in the database for the parameter.
x_{max} : maximum values in the database for the parameter

Train, check and test sets selected randomly and optimum structure of ANFIS model are determined. Two methods are commonly used to generate ANFIS: Grid-Partition (GP) and Subtractive-Clustering (SC). ANFIS with GP algorithm uses a hybrid learning algorithm to identify parameters of inference system. It applies a combination of the least-squares method and the back propagation gradient descent method for training ANFIS membership function parameters. Clustering is a task of assigning a set of data into groups called cluster to discover structures and patterns in a dataset. The SC method assumes that each data point is a potential cluster center and calculates a measure of likelihood that each data point would define the cluster center, based on the density of surrounding data points. In SC method, range of influence of the data must be defined before create the model. This parameter used to estimation of the radius of cluster for generate ANFIS.

After developing several models with different structures, the optimum structure is determined. The final optimum structure of the ANFIS model was using SC method for generating ANFIS with 9 fuzzy rules for the Gaussian function with 5 membership function for any of input parameters. Range of influence for SC considered 0.17. The results of the test phase for the selected model of ANFIS have RMSE (root mean squared errors) and MAE (mean absolute errors) about 0.15% and correlation factor (R^2) 98% and it showed that ANFIS had acted very well in prediction.

8. SEISMIC MOMENT PREDICTION

Figs. 5-9 show the results of the ANFIS for all 493 test data. The blue line in the figures show observed data and the red line shows the predicted values. It seems that the output of ANFIS has very good coincidence with the real observed data.

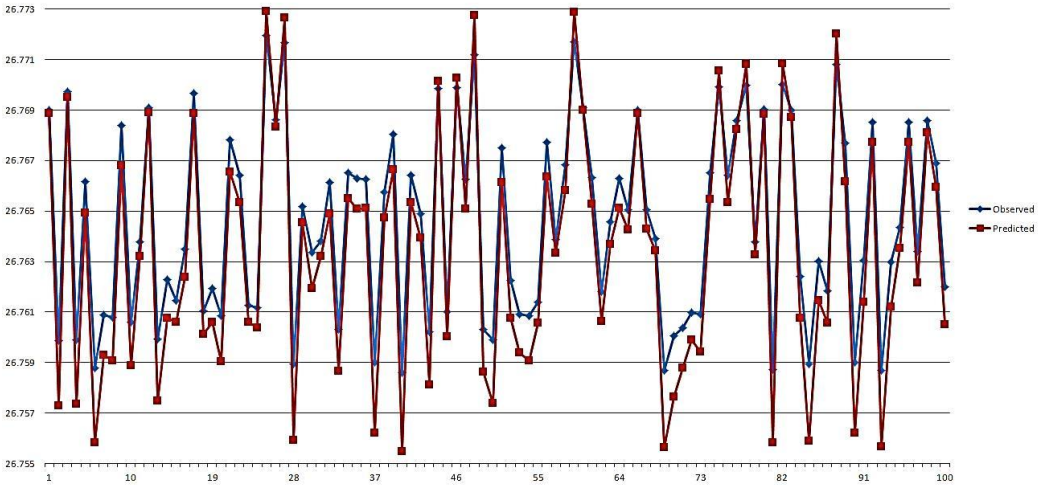

Figure 5. The obtained results by ANFIS for the test data number 1 to 100

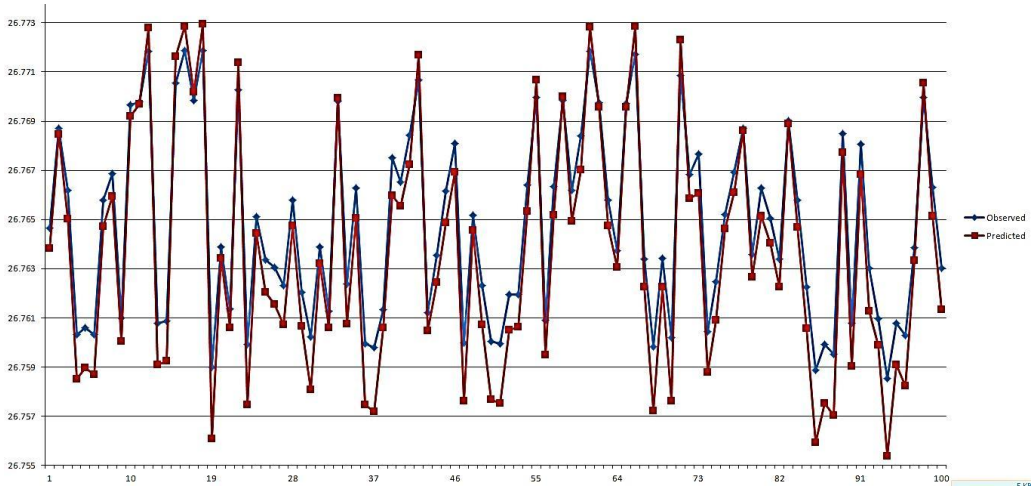

Figure 6. The obtained results by ANFIS for the test data number 101 to 200

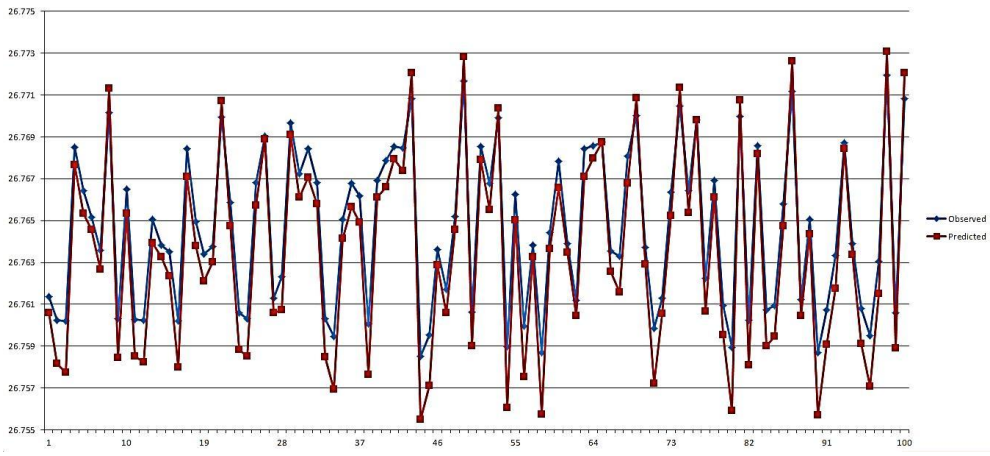

Figure 7. The obtained results by ANFIS for the test data number 201 to 300

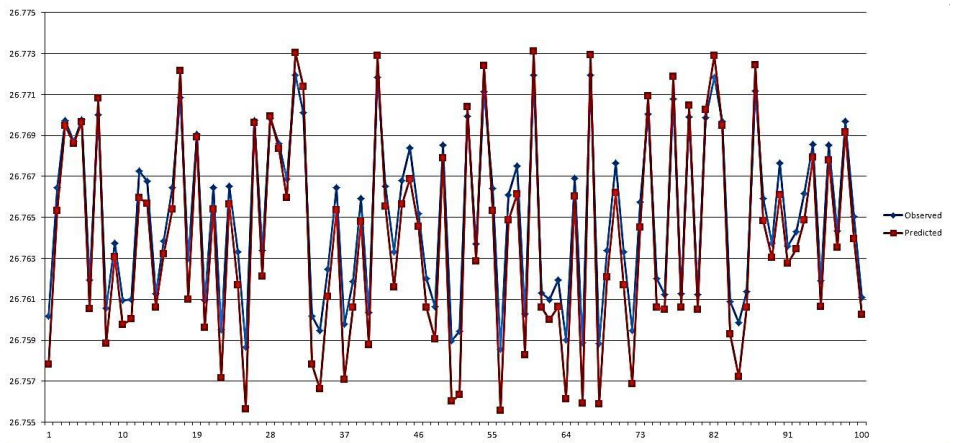

Figure 8. The obtained results by ANFIS for the test data number 301 to 400

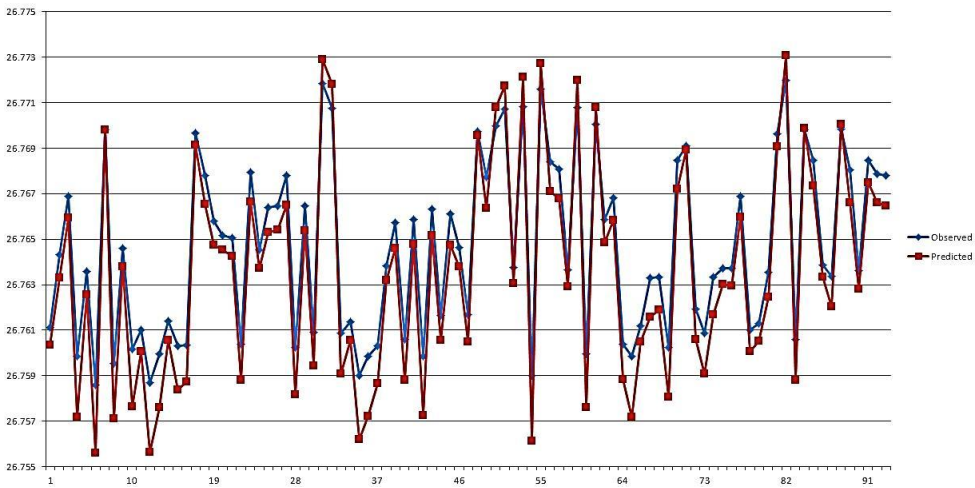

Figure 9. The obtained results by ANFIS for the test data number 401 to 493

The considered output of the ANFIS was logarithm of the cumulative seismic moment between the origin record (the first record of the dataset which is occurred in origin time) and the next earthquake of each event (LMCN). With converting LMCN to non-logarithmic amount for each record, the final result which is the released cumulative seismic moment between each record and the next event was obtained.

In the non-logarithmic mode, amount of error is more than logarithmic mode, but the correlation factor for the predicted amount which is calculate from the obtained results by ANFIS is 98% that is not negligible. The seismic moment is one of the important seismic indicators that use for evaluating an earthquake. Prediction of this indicator can help to predictors to find other qualities of the next earthquake such as magnitude or released energy.

9. CONCLUSIONS

In this paper, it was endeavored to study the ability of ANFIS in predicting earthquake. To do so, data of Iranian catalogue was used. The ANFIS model created by two inputs mean the time from origin (TO) and logarithm of mean annual rate of exceedance (LLm) with logarithm of cumulative seismic moment between the origin time and the next earthquake of each event (LMCN) as an output. Factors which cause error in this model can be stated as follows:

- If an earthquake is not recorded, its seismic moment will not be accounted in the process of computation of cumulative LMCN. A lot of earthquakes particularly those occurred before 1975 are not recorded in Iran. Considering the fact that there is a direct relation between output of the model and amount of cumulative seismic moment, omission of an earthquake has a direct effect on results.
- Lack of uniformity in seismic catalogue made the authors use available regression equations. These equations which are used to determine moment magnitude of earthquake records followed by calculating seismic moment can be a reason for error.
- Results obtained from test phase, having correlation factor of 98 percent and MAE and RMSE about 0.15% showed that the ability of ANFIS for prediction earthquake is good. Present study as one of the several researches that investigated the application of artificial intelligent model for predicting earthquake, has yielded good results.

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