Application of neural network based on genetic algorithm in predicting magnitude of earthquake in North Tabriz Fault (NW Iran)

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Here we present an application of a supervised feed forward artificial neural network (ANN) that is trained on the basis of genetic algorithm (GA). The network model is used for predicting the magnitude of earthquakes in the North Tabriz Fault (NTF) Northwest Iran. The earthquake database was derived from the catalogues of both the International Institute of Earthquake Engineering and Seismicity of Iran and the Iranian Seismological Center. For this purpose, three temporal seismicity parameters were calculated using the ZMAP MATLAB toolbox. The performance of the artificial neural network (ANN) model was measured in terms of accuracy by a ten-fold cross-validation as 99.11%. Another evaluation method was predicting a case event that occurred on 11 August 2012 in Ahar-Varzeghan in Iran. Results showed that the ANN optimized with GA (ANNGA) learning optimization model is suitable and may be useful for predicting future earthquakes, especially in active seismologic regions.

Keywords: Artificial neural network, earthquake magnitude, genetic algorithm, temporal seismicity features.

THE northwest of Iran is one of the most active seismic regions of the country with many seismic events over the past and recent years. The North Tabriz Fault (NTF) is one of the most interesting faults of Iran with the two of the most destructive historical earthquakes that occurred in 1721 and 1780 (refs 1, 2). Some studies have shown that re-occurrence interval of high-magnitude earthquakes for NTF is about 250–300 years. Recent earthquakes that occurred around this region imply high probability for the recurrence of high-magnitude earthquakes[3,4]. One of the recent earthquakes with magnitude 6.3–6.4 on the Richter scale (IIEES reported 6.5) occurred on 11 August 2012 in Ahar that is situated in the NTF region, causing huge destruction and considerable fatalities (300 deaths)[5]. Recently, probabilistic hazard assessment based on ground motions has been implemented to construct a seismic hazard map for predicting return period of the earthquakes[6]. Vafaie *et al.*[7], based on the iso-acceleration maps have shown that the probabilities of earthquake occurrence at intervals of 72, 475, 2475 years is 63%, 10% and 2% respectively[7]. The target region under study is enclosed between 45–48°E long. and 37–39°N lat. (refs 7–9). Despite the prediction of the year in which destructive earthquakes are likely to occur, confidence level of predictions is also important to achieve satisfactory results. The problem of earthquake prediction has been often reported as an important research topic for geologists during the recent years to manage possible occurrence of disasters[10,11]. For this purpose, two important factors need to be considered: (1) selection of algorithms implemented in the intelligent systems (e.g. which may be single or hybrid), and (2) availability of extracted features based on environmental, temporal, and spatial properties of soil (e.g. radon concentration)[12], latitude, time of occurrence and longitude of a disaster[13]. Analysis of seismic activities in terms of temporal and spatial events is a difficult problem attracting the attention of seismologists to propose statistical models for predicting the occurrence time of the earthquakes[14]. The applications of artificial neural network (ANN)[15,16] in this area are numerous. Many researchers have carried out studies based on ANNs as they enable us to learn linear or nonlinear nature of functions. The nature of the earthquake is defined as a nonlinear function[13]. Most types of feed forward ANNs have at least three layers, namely input, hidden and output layers. Each layer has several neurons with weights, biases and activation functions assigned to them. Various types of ANNs which attempt to mimic the capabilities of the human brain have been trained, based on several learning algorithms (e.g. Levenberg–Marquardt (LM), genetic algorithm (GA), etc.) to leverage the errors between the desired and predicted output values. The ANNs have been increasingly applied to many fields of earth sciences ranging from predicting the magnitude of earthquakes to understanding their patterns using several types of neural networks[12,13,17–26].

Recently, Zamani *et al.*[13] used seismicity parameters of Qeshm earthquake for learning two types of intelligent systems (i.e. Radial Basis Function (RBF) ANN and Adaptive Neuro Fuzzy Inference System (ANFIS) model) to predict spatio-temporal variations of earthquakes. Input data were pre-processed using principal component analysis (PCA) techniques to be fed as inputs to the proposed intelligent system. They have reported that their proposed model is able to predict the epicentre area and time of occurrence of the chief and destructive quake that shook Qeshm in 2008 (ref. 13). There are other studies which also took advantage of spatio-temporal variations of seismicity for investigating the earthquakes that occurred in the two cities of Izmit and D¨uzce, as well as in Australia[27,28]. Zhang and Wang[24] used two types of ANNs: (1) the back propagation (BP)-ANN and (2) GA-based ANN, for optimizing and predicting the magnitude of the earthquakes. Zhou and Zhu[17] proposed a BP-ANN for predicting magnitude of earthquakes which

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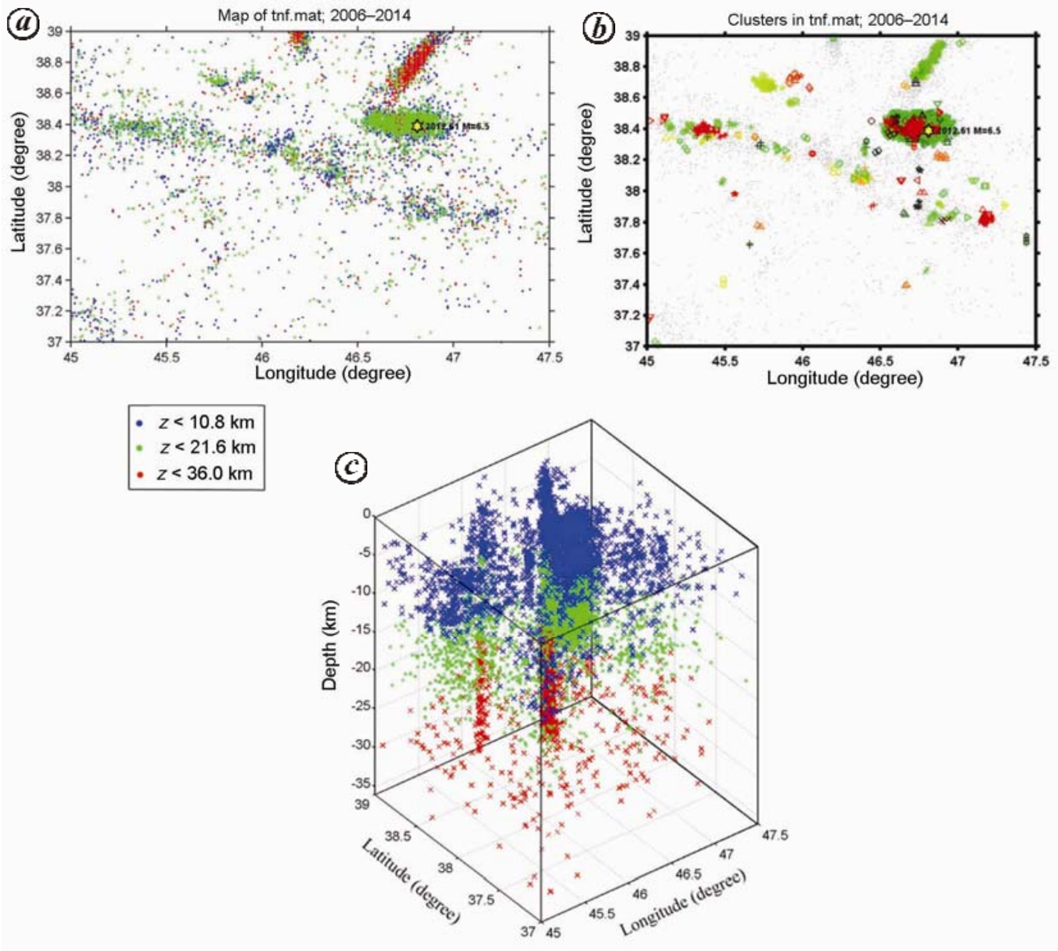

Figure 1. Epicentre map of all earthquake data between 2006 and 2013. ***a***, The epicenter of the 11 August 2012, Ahar main shock is shown by star. ***b***, Data declustered using Reasenberg algorithm. ***c***, Three-dimensional schematic of data under investigation.

were trained based on LM algorithm. Their results showed the effectiveness, fast convergence, and high precision of their tool for predicting the magnitude of earthquakes[17]. Niksarlioglu and Kulahci[18] proposed a method which employed clustering and neural network techniques along with environmental mapping of seismic activity for their predictions. They used nine parameters for their ANN input, including latitude, longitude, radon, steam pressure, temperature of soil at depth of 10, 20 and 50 cm and wet/dry bulb temperature[18,23]. However, Zamani *et al.*[13] used eight parameters, including five seismic and three spatial analysis parameters available in the ZMAP MATLAB toolbox implemented by Wiener in 2001 (ref. 29). Panakkat and Adeli[25] used a recurrent ANN and a simple ANN to approximate the time and location of the future earthquakes using multiple seismicity indicators (for more information, one may refer to Panakkat[21].

In the present communication the temporal parameters of NTF seismicity properties associated with the 11 August 2012 Ahar earthquake ($M = 6.5$ (IIEES) or 6.3–6.4) in the northwest of Iran have been studied using ANN trained by GA to predict magnitude of future earthquakes based on temporal characteristics. This study could be considered as fresh attempt at investigating assessment and prediction in the NTF seismic region.

In order to access the seismic database on the NTF area, catalogues of IIEES of Iran and Iranian Seismological Center (ISC), which are known to include clear and errorless data were considered (available at http://irsc.ut.ac.ir/bulletin.php). The rectangular area between 45–48°E long. and 37–39°N lat. at the centre of which the city of Tabriz (38.073°N, 46.292°E) is located, is considered as the region of study. Data are for time interval of 1 January 2006 to 29 December 2013 and include 10103 and 626 earthquake events respectively, for both databases mentioned. The epicentre of the NTF region is located at a depth of 15 km (ref. 30). Available data for the period between 2000 and 2006 were less in IIEES and not available in ISC; consequently they were discarded. Both databases were combined and four earthquake events of IIEES lacking the depth parameter and the remaining

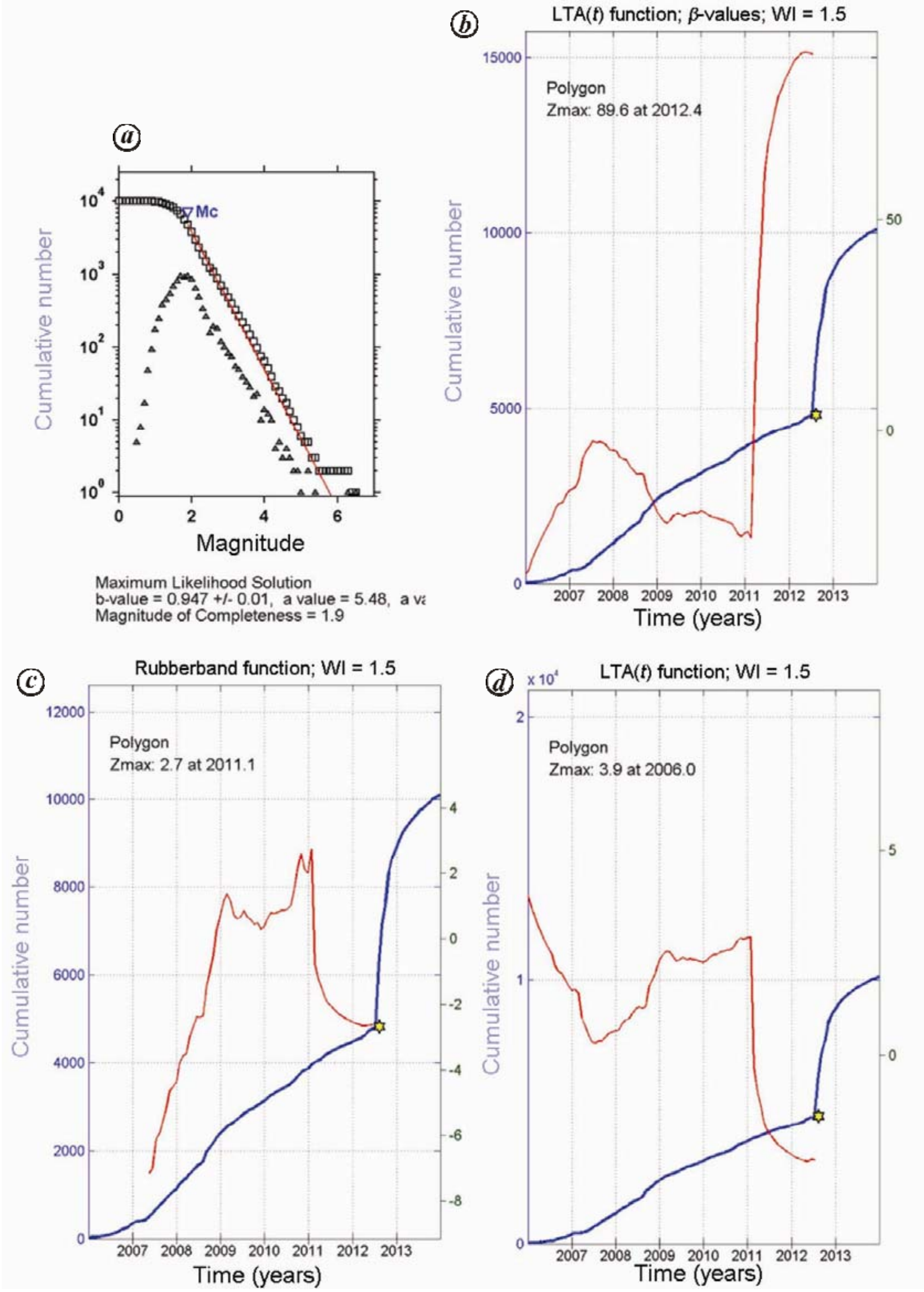

Figure 2. ***a***, The Gutenberg–Rishter magnitude–frequency relation of earthquakes for 11 August 2012 that is used for temporal analysis. ***b***, Calculation of β value of long time average (LTA) function using LTA algorithm. ***c***, *z* values of rubberband. ***d***, *z* values of LTA functions.

ones from ISC were included; so a total of 10,103 earthquake events were considered in the study (Figure 1 *a*). The collected earthquake data have five features: longitude, latitude, magnitude, depth and time of each event.

ZMAP MATLAB toolbox[29] receives earthquake data as input and produces output record with two types of spatial and temporal features. In our study, temporal features are more important and, therefore, only these are considered as main features. They are used as inputs of the intelligent system to achieve the desired prediction values. These features include temporal properties (i.e. β value of long time average (LTA) function using the LTA algorithm[31,32], and z values of rubberband and LTA functions[27,33]) considered as an input vector in the preprocessing stage (Figure 2 *b–d*). During data collection, as magnitude of completeness (M_c) is an important factor to be considered for all of the seismic activities, the maximum curvature method was set to 100 bootstrap runs in the ZMAP toolbox. Therefore, Mc value was 1.9 for the dataset studied and data with Mc values lower than 1.9 were omitted (Figure 2 *a*). Then, the whole data were de-clustered based on the Reasenberg algorithm. Finally, the dataset of earthquake events was left with only 6189 events (Figure 1 *b* and 3D representation of data in Figure 1 *c*). During the de-clustering process, 195 clusters were identified and 4109 out of 10,103 events could be considered as representative of the remaining 6189 events as shown in Figure 1 *b*. In this figure, individual clusters are shown in magenta colour and marked 'o'. The temporal distribution of earthquake activities is shown in Figure 3 for the time-period of the present study. The whole data were also normalized in order to satisfy the conditions of zero mean and unity variance. Unlike other studies applying a dimensionality reduction algorithm such as principle component analysis (PCA) and singular value decomposition (SVD), here we did not use these methods due to their drawbacks when applied to data with small-dimension features. All data were analysed, with the input vector of ANN consisting of three features and the predicted output data were the magnitude value of the earthquake event. These were prepared for training and optimizing the feed forward ANN using GA in order to minimize the mean squared error (MSE) between the desired and predicted output values. Figure 4 summarizes the overall procedures in the present study.

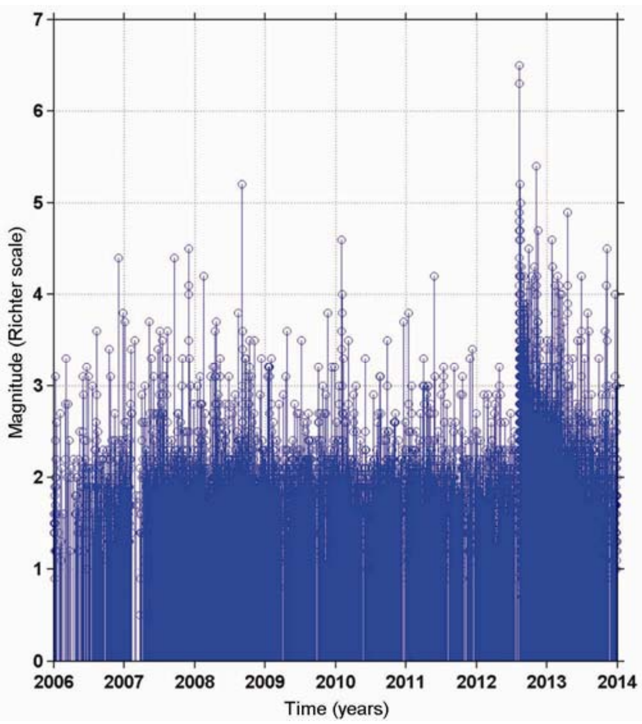

Figure 3. Temporal distribution of earthquake activities in the time period of the present investigation.

To calculate the three parameters related to the earthquake events, their plots as to the cumulative numbers of events versus time in years were drawn using the ZMAP toolbox (Figure 2 *b–d*). The 'bin' length was determined to be 14 days. After the temporal parameters were calculated, three time-series plots were drawn, each of which contained 209 sample points (i.e. $3 \times 209 = 627$ sample points in total). Ten-fold cross-validation was carried out to validate the model using temporal features. Nine random groups containing 63 sample events with only one containing 60 sample events were used for the training and testing stages respectively. At the end, the average of all ten runs was calculated as the overall performance of the model in terms of accuracy value.

The output values of magnitudes were considered as below:

If (binlength = 14 days) and (desired magnitude < M_c) then (magnitude = M_c) else Magnitude = desired magnitude.

To implement the GA-ANN, 'ANN' package by Roy-Desrosiers[34] was used in R software[35]. Command 'ANNGA' was used to implement the ANN network, which was then optimized by GA to improve speed, convergence and memory management. An ANN is a mathematical and computational model that is composed of neurons and connections between neurons known as synapses or connection weights. ANN is inspired by the human brain which has the capability of learning and recognizing complex linear and/or nonlinear relationships between input and output values of functions[36–38]. The type of neural network that is used in the present study is supervised and feed forward. In supervised learning for each input value, the desired output values are available and ANN adjusts its synaptic weight to adapt to the desired functionality. Feed forward ANN takes an input vector in the input layer and forwards it to the neurons of hidden layers to reach the neuron at the output layer without having any information feedback. The proposed ANN model has four layers, including one input, two hidden, and one output layer. The input layer takes three features of each event. For each neuron, an extra bias input with value +1 is considered. Each neuron computes the weighted sum of all its inputs (containing bias) by summing the product of input signals with associated synaptic weights. Then, activation function is applied on this sum for producing output result of each neuron. After

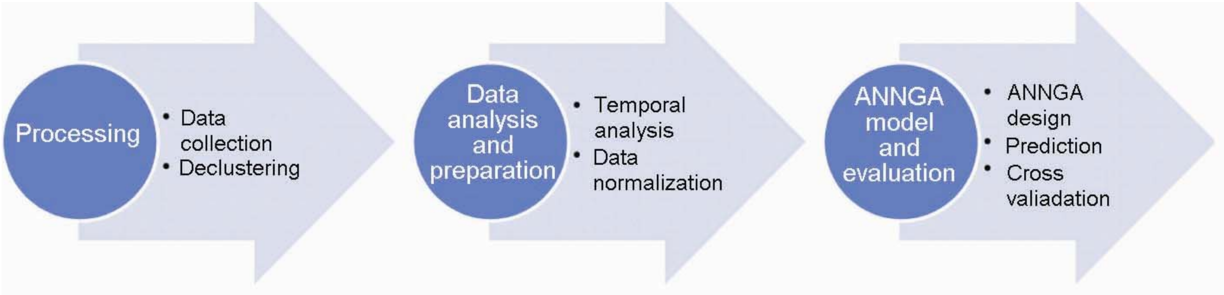

Figure 4. Diagram showing the earthquake prediction methodology.

the results are received in the hidden layer, they will be processed and their outputs in turn will be distributed to the next layer. At the end, the output neuron processes the information received from the last hidden layer. In all layers, the sigmoid activation function (i.e. $x = 1/(1 + e^{-x})$) is used in this package. The formula of the designed four-layered feed forward neural network is as below:

$$f\left(\sum_{k=1}^{N\text{ hidden layer 2}} w_{3,k,1}\, f\left(\sum_{j=1}^{N\text{ hidden layer 1}} w_{2,j,k}\right.\right.$$

$$\left.\left. f\left(\sum_{i=1}^{N\text{ hidden layer 3}} w_{1,i,j}\,\text{input}_i + \text{bias}_{1,j}\right) + \text{bias}_{2,k}\right) + \text{bias}_{3,1}\right)$$

$$= \text{output}, \qquad (1)$$

where $w_{a,b,c}$ demonstrates the weight from bth neuron of ath layer to the cth neuron of the next layer. The bias is a constant +1 value for neurons of all layers and it is computed along with the synaptic weights. The mean squared error (MSE), which is the error between the desired and the predicted outputs, must be minimized according to the equation

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{\text{patterns number}} (y_i^{\text{desired output}} - y_i^{\text{predicted output}})^2.$$

The minimization algorithm for MSE is GA, an evolutionary method for predicting the weights of a neural network constituting the chromosomes. All of the GA stages, including generation of chromosomes, mutation and crossover are present in this process. The mutation formula for generating a new weight is

$$w_{j,i}^{\text{new}} = w_{k,i} + \text{Mutation rate} * (w_{m,j} - w_{n,i}). \qquad (2)$$

Crossover is performed based on the probability of crossover rate for changing the weights in each chromosome. If the MSE of the new chromosome is less than the old one, GA will replace the new weights until the desired MSE is satisfied. After the data are loaded in the R workspace, the ANNGA will run with the following settings to reach the best-trained ANN model (Figure 5) with a desired MSE value of 0.001:

ANNGA (x = Input-vector, y = Desired-output, design = c(3,6,6,1), population = 500, mutation = 0.2, crossover = 0.6, maxGen = 5000, error = 0.001).

In the northwest of Iran, a destructive earthquake shook Ahar-Varzeghan with magnitude M_w 6.4 and 6.3 on 11 August 2012 at 12 : 23 and 12 : 34 UTC respectively[5]. Its epicentre was located at 46.81 N, 38.39 E. More than 300 people died and over 3000 people were left injured[5,39] due to this earthquake.

In our previous studies[40], the clustering variations of the earthquake events of the NTF region were reported based on the results of different clustering methods. The seismicity parameters were latitude, longitude, date, time of occurrence and magnitude. Furthermore, the assessments were performed on stability, accuracy and robustness of several clustering techniques. The results showed that the earthquake data belonging to the region studied were totally complex and nonlinear. However, knowledge-based relationships among the features were derived based on the intelligent system that was used for modelling. The results showed that an optimal number of clusters are achievable while studying several types of clustering techniques. The study of temporal seismicity parameters provides significant insight into the prediction of magnitude of earthquake events.

The ANNGA was trained using a 3 × 189 matrix (i.e. three neurons) in the input layer and a 1 × 189 matrix (i.e. one neuron) in the output layer. Each event provides data for three input nodes of ANNGA with the corresponding magnitude value as the desired output following a time-series approach. The training data are provided randomly to satisfy the generalizability property of the trained model. The model has been trained ten times with the desired MSE value lower than 0.001. Ten ANNGA network models are created for testing ten sets of 3 × 20 matrices of magnitude values. The correlation between the desired

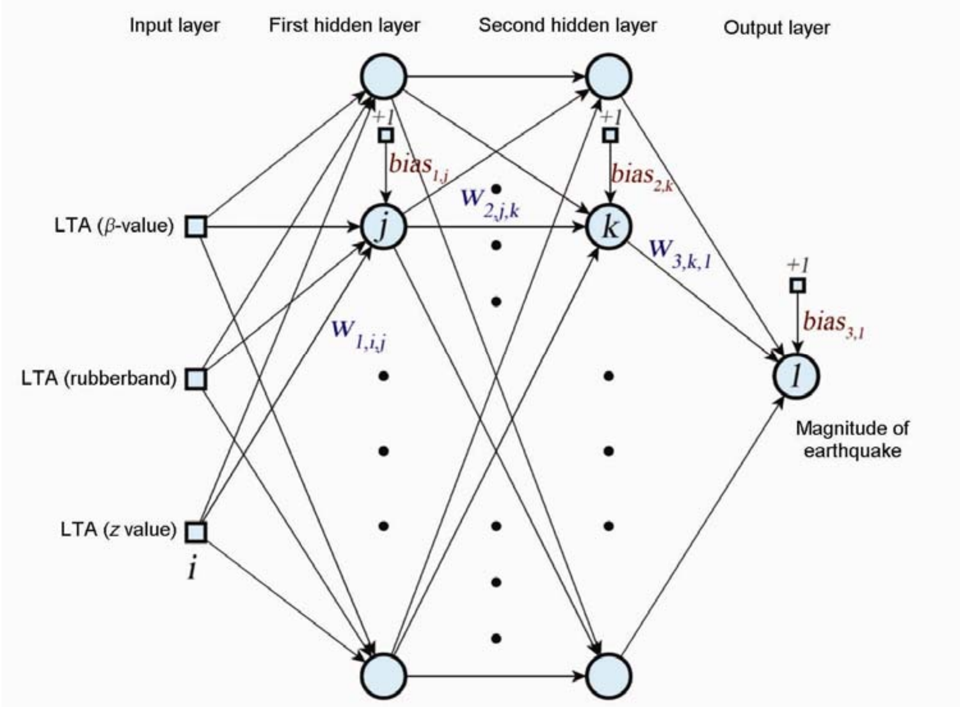

Figure 5. The proposed ANN optimized by GA model.

Table 1. Performance results of ANN optimized by GA model during evaluation of temporal analysis results

ANNGA group sets	MSE	R^2
Group 1	0.000995	0.9875
Group 2	0.000876	0.995
Group 3	0.000895	0.9885
Group 4	0.0009	0.9823
Group 5	0.00088	0.9962
Group 6	0.00065	0.9986
Group 7	0.00098	0.9901
Group 8	0.000787	0.9892
Group 9	0.000857	0.9851
Group 10	0.000865	0.9984
Total cross-validation	0.00868	0.9911

and the predicted outputs was 0.9911 when the correlation values of ten testing results were averaged. Moreover, the average MSE was 0.00868 (Table 1). The number of neurons and hidden layers was determined and optimized based on the results obtained during the running stages. Two hidden layers with six neurons in each layer yielded the best results. The data for the case study (i.e. 11 August 2012) were included in one of the testing sets and checked for their validity. The magnitude value related to the case study showed that ANNGA was also able to predict its value accurately.

In this study, no dimensionality reduction algorithms were applied. Although covering the whole temporal features is clearly beneficial, using PCA or SVD, only less than 80% of the data can be covered and that affects the prediction performance of the ANNGA model. In the study carried out by Zamani *et al.*[13], the PCA algorithm covers only a portion of the data (i.e. less than about 70%); thus it is not possible to achieve a high accuracy in prediction. In other words, the dimensionality reduction algorithm has advantages on visualizing the data when the smallest number of components covers about 80–90% of the total dataset and ignores the principal components whose eigenvalues are less than average (i.e. less than 1 if the correlation matrix is used). Moreover, PCA should not be applied on the uncorrelated data. This means that the PCA performed on the temporal data in the study by Zamani *et al.*[13] will result in reducing the number of features for the sake of lowering prediction accuracy[41]. Last but not least, it is worth mentioning that PCA or SVD methods for data reduction must be used carefully and all conditions of their applicability should be checked and satisfied before being applied to a small or large database.

The pattern recognition on the nonlinear and complex seismicity problems to estimate the large magnitude values of earthquakes is gaining attention of seismologists because of multiple variables affecting this phenomenon. Understanding each of these complex variables plays an important role in making correct predictions by intelligent models. In this study, temporal characteristics of earthquakes were calculated and used as a three-feature vector in a feed forward ANN model trained by GA to minimize the MSE defined as its fitness function. The results show that the temporal properties of seismic events can not only predict the remaining unseen magnitude values of the events correctly, but are also capable of determining the main earthquake occurring in the case study as well. However, to increase the accuracy of the earthquake predictor for the NTF region, the data were normalized and no dimensionality reduction algorithm was applied because it had no coverage higher than 80–90% of small features. While analysing the temporal features of seismic events, two types of evaluation methods were employed, including the ten-fold cross-validation technique and examining the forthcoming event of 11 August 2012 (i.e. Ahar-Varzeghan earthquake). The ANNGA model was successfully performed on both types of assessments and was also able to correctly predict the main shock occurring in the time span of 11 August 2012.

The accuracy of the ANNGA was evaluated using ten-fold cross-validation to prove its generalizability and avoid overtraining issues. The MSE values of the intelligent model were minimized using GA. The accurate results show that the ANNGA model can be considered a robust tool for recognizing the patterns of seismic regions and is an effective mathematical model for assessing and mitigating the results of the large earthquakes in the future. Moreover, the satisfactory results obtained by this model can be regarded as useful grounds for application to other seismic areas for robust and accurate predictions of future earthquake events.

Finally, despite the high accuracy of performance of the proposed model, the need for an accurate and complete catalogue of earthquakes in the NTF region is essential. To reach this goal, more professional earthquake sites is required in this region. Additionally, more event parameters can be included in future studies through the inclusion of chemical features (e.g. radon measurements, etc), weather parameters and pressure properties.

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